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**Research Paper
RM-293**

Scaling of Ratings: Concepts and Methods

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$$MR_i = \frac{1}{n} \sum_{j=1}^{n} R_{ij}$$

$$Z_{ij} = (R_{ij} - MR_j) / SDR_j$$

$$SBE_{jc} = (MZ_{jc} - BMZ_j)\ 100$$

$$LSR_{ij} = a_j + b_j R_{ij}$$

$$OAR_{ij} = R_{ij} - MR_j$$

$$C_k - S_i = \Phi^{-1}(CP_{ik})\ \alpha$$

Abstract

Rating scales provide an efficient and widely used means of recording judgments. This paper reviews scaling issues within the context of a psychometric model of the rating process and describes several methods of scaling rating data. The scaling procedures include the simple mean, standardized values, scale values based on Thurstone's Law of Categorical Judgment, and regression-based values. The scaling methods are compared in terms of the assumptions they require about the rating process and the information they provide about the underlying psychological dimension being assessed.

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Scaling of Ratings: Concepts and Methods

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INTRODUCTION

Rating scales offer an efficient and widely used means of recording judgments about many kinds of stimuli. Such scales are often used in studies relating to natural resources management, for example, to measure citizen preferences for recreation activities (Driver and Knopf 1977) or perceived scenic beauty of forest scenes (Brown and Daniel 1986). In this paper we review issues regarding the use of rating data, and describe and compare methods for scaling such data.

This paper provides theoretical and descriptive background for scaling procedures available in a computer program called RMRATE, which is described in a companion document (Brown et al. 1990). RMRATE is designed to (1) scale rating data using a battery of scaling procedures, (2) compare the scale values obtained by use of these procedures, (3) evaluate to a limited extent whether the assumptions of the scaling procedures are tenable, (4) determine the reliability of the ratings, and (5) evaluate individual variations among raters.

Both this paper and the RMRATE computer program are outgrowths of an effort that began in the early 1970s to better understand the effects of management on the scenic beauty of forest environments. An important report by Daniel and Boster (1976) introduced the Scenic Beauty Estimation (SBE) method. The SBE method is reviewed and further developed herein, along with other scaling procedures, including median and mean ratings, standardized scores, and a new scale based on a least squares analysis of the ratings.

While scenic beauty has been the focus of the work that led up to this paper, and continues to be a major research emphasis of the authors, the utility of the scaling procedures is certainly not limited to measurement of scenic beauty. Rather, this paper should be of interest to anyone planning to obtain or needing to analyze ratings, no matter what the stimuli.

Psychological scaling procedures are designed to deal with the quite likely possibility that people will use the rating scale differently from one to another in the process of recording their perceptions of the stimuli presented for assessment. Scaling procedures can be very effective in adjusting for some of these differences, but the procedures cannot correct for basic flaws in experimental design that are also reflected in the ratings. While aspects of experimental design are mentioned throughout this paper, we will not cover experimental design in detail; the reader desiring an explicit treatment of experimental design should consult a basic text on the topic, such as Cochran and Cox (1957) or Campbell and Stanley (1963).

We first offer a brief introduction to psychological scaling to refresh the reader's memory and set the stage for what follows. Readers with no prior knowledge of scaling methods should consult a basic text on the subject, such as Nunnally (1978) or Torgerson (1958). We then describe and compare several procedures for scaling rating data. Finally, additional comparisons of the scaling procedures are found in the appendix.

PSYCHOLOGICAL SCALING

Psychometricians and psychophysicists have developed scaling procedures for assigning numbers to the psychological properties of persons and objects. Psychometricians have traditionally concentrated on developing measures of psychological characteristics or traits of persons, such as the IQ measure of intelligence. Psychophysics is concerned with obtaining systematic measures of psychological response to physical properties of objects or environments. A classic example of a psychophysical scale is the decibel scale of perceived loudness.

Among the areas of study to which psychophysical methods have been applied, and one that is a primary area of application for RMRATE (Brown et al. 1990), is the scaling of perceived environmental quality and preferences. In this context, scaling methods are applied to measure differences among environmental settings on psychological dimensions such as esthetic quality, scenic beauty, perceived naturalness, recreational quality, or preference.

Scaling Levels

An important consideration in psychological scaling, as in all measurement, is the "level" of the scale that is achieved. Classically there are three levels that are distinguished by the relationship between the numbers derived by the scale and the underlying property of the objects (or persons) that are being measured. The lowest level of measurement we will discuss is the *ordinal* level, where objects are simply ranked, as from low to high, with respect to the underlying property of interest. At this level, a higher number on the scale implies a higher degree (greater amount) of the property measured, but the magnitude of the differences between objects is not determined. Thus, a rank of 3 is below that of 4, and 4 is below 6, but the scale does not provide information as to whether the object at rank 4 differs more from the object at 3 or from the object ranked at 6. At this level of measurement only statements of "less than," "equal to," or "greater than," with respect to the underlying property, can be supported.

Most psychological scaling methods seek to achieve an *interval* level of measurement, where the magnitude of the difference between scale values indicates, for example, the extent to which one object is preferred over another. The intervals of this metric are comparable over

the range of the scale; e.g., the difference between scale values of 1 and 5 is equivalent to the difference between 11 and 15 with respect to the underlying property. Interval scale metrics have an arbitrary zero point, or a "rational" origin (such as the Celsius scale of temperature where 0 degrees is defined by the freezing point of water). They do not, however, have a true zero point that indicates the complete absence of the property being measured.

Interval scales will support mathematical statements about the magnitude of *differences* between objects with respect to the property being measured. For example, a statement such as "a difference of 4 units on the measurement scale represents twice as great a difference in the underlying property as a difference of 2 units" could be made about information in an interval scale. It would not be permissible, however, to state that "the object with a value of 4 has twice as much of the property being measured as the object scaled at 2." The latter statement requires a higher level of measurement, one where all scale values are referenced to an "absolute zero."

The highest level of measurement is the *ratio* scale, where the ratios of differences are equal over the range of the scale; e.g., a scale value of 1 is to 2 as 10 is to 20. Ratio scales require a "true zero" or "absolute" origin, where 0 on the scale represents the complete absence of the property being measured (such as the Kelvin scale of temperature, where 0 represents the complete absence of heat). Generally, ratio scales are only achieved in basic physical measurement systems, such as length and weight. Absolute zeros are much harder to define in psychological measurement systems, because of the difficulty of determining what would constitute the absolute absence of characteristics such as intelligence or preference.

It is important to note that the ordinal, interval, or ratio property of a measurement scale is determined with reference to the underlying dimension being measured; 20 degrees Celsius is certainly twice as many degrees as 10, but it does not necessarily represent twice as much *heat*.

The level of measurement may place restrictions on the validity of inferences that can be drawn about the underlying property being measured based on operations performed on the scale values (the numbers). Some frequently used mathematical operations, such as the computation and comparison of averages, require assumptions that are not met by some measurement scales. In particular, if the average of scale values is to represent an average of the underlying property, then the measurement scale must be at least at the interval level, where equal distances on the measurement scale indicate equal differences in the underlying property. Similarly, if ratios of scale values are computed, only a ratio scale will reflect equivalent ratios in the underlying property.

Scaling Methods

A number of different methods can be used for psychological scaling. All methods involve the presentation of objects to observers who must give some overt indication of the relative position of the objects on some designated psychological dimension (e.g., perceived weight, brightness, or preference). Traditional methods for obtaining reactions to the objects in a scaling experiment include paired-comparisons, rank orderings, and numerical ratings.

Perhaps the simplest psychophysical measurement method conceptually is the method of *paired-comparisons*. Objects are presented to observers two at a time, and the observer is required to indicate which has the higher value on the underlying scale; e.g., in the case of preferences, the observer indicates which of the two is most preferred. A related procedure is the *rank-order* procedure. Here the observer places a relatively small set of objects (rarely more than 10) in order from lowest (least preferred) to highest (most preferred). At their most basic level, these two procedures produce ordinal data, based on the proportion of times each stimulus is preferred in the paired-comparison case, and on the assigned ranks in the rank-ordering procedure.

One of the most popular methods for obtaining reactions from observers in a psychological measurement context uses *rating scales*. The procedure requires observers to assign ratings to objects to indicate their attitude about some statement or object, or their perception of some property of the object.

In each of these methods, the overt responses of the observers (choices, ranks, or ratings) are not taken as direct measures of the psychological scale values, but are used as *indicators* from which estimates of the psychological scale are derived using mathematical procedures appropriate to the method. In theory, the psychological scale values derived for a set of objects should not differ between different scaling methods. For example, if a paired-comparison procedure and a rating scale are used for indicating relative preferences for a common set of objects, the psychological preference scale values for the objects should be the same, or within a linear transformation.

While the basic data from the paired-comparison and rank-order procedures are originally at the ordinal level of measurement, psychometric scaling procedures have been developed that, given certain theoretical assumptions, provide interval level measures. Perhaps the best known procedures are those developed by Thurstone (see Nunnally (1978) and Torgerson (1958)), whereby choices or ranks provided by a number of observers (or by one observer on repeated occasions) are aggregated to obtain percentiles, which are then referenced to a normal distribution to produce interval scale values for the objects being judged. A related set of methods, also based on normal distribution assumptions, was developed for rating scale data. Later sections of this paper describe and compare procedures used with rating data. Additional, more detailed presentations of the theoretical rationale and the computational procedures are found in the texts by authors such as Torgerson (1958) and Nunnally (1978). Discussion of these issues in the context of landscape preference assessment can be found in papers by Daniel and Boster (1976), Buhyoff et al. (1981), and Hull et al. (1984).

Rating Scales

Rating response scales are typically used in one of two ways. With the first approach, each value of the rating scale can carry a specific descriptor. This procedure is often used in attitude assessment. For example, the values of a 5-point scale could be specified as (1) completely agree, (2) tend to agree, (3) indifferent, (4) tend to disagree, and (5) completely disagree, where the observer is to indicate degree of agreement about a set of statements. The observer chooses the number of the response that most closely represents his/her attitude about each statement. With the second use of rating scales, only the end-points of the scale are specified. This format is commonly used with environmental stimuli. where observers are required to assign ratings to stimuli to indicate their perception of some property of the stimuli. For example, a 10-point rating scale might be used, with a "1" on the scale indicating "very low preference" for the stimulus, and a "10" indicating "very high preference." Ratings between 1 and 10 are to indicate levels of preference between the two extremes. The end-points are specified to indicate the direction of the scale (e.g., low ratings for less preference, high ratings for more preference).

Whether associated with a specific descriptor or not, an individual rating, by itself, cannot be taken as an indicator of any particular (absolute) value on the underlying scale. For example, labeling one of the categories "strongly agree" in no way assures that "strong" agreement in one assessment context is equivalent to "strong" agreement in another. Similarly, a rating of "5" by itself provides no information. A given rating provides useful information only when it is compared with another rating; that is, there is meaning only in the relationships among ratings as indicators of the property being assessed. Thus, it is informative to know that one stimulus is rated a 5 when a second stimulus is rated a 6. Here the ratings indicate which stimulus is perceived to have more of the property being assessed. Furthermore, if a third stimulus is rated an 8, we *may* have information not only about the ranking of the stimuli, but also about the degree to which the stimuli are perceived to differ in the property being assessed.

Ratings, at a minimum, provide ordinal-level information about the stimuli on the underlying dimension being assessed. However, ratings are subject to several potential "problems" which, to the extent they exist, tend to limit the degree to which rating data provide interval scale information and the degree to which ratings of different observers are comparable. Before we review some of these problems, it will be useful to present a model of the process by which ratings are formed and scaled.

Psychometric Model

The objective of a rating exercise is to obtain a numerical indication of observers' perceptions of the relative position of one stimulus versus another on a specified psychological dimension (e.g., scenic beauty). This objective is approached by two sequential procedures (fig. 1).

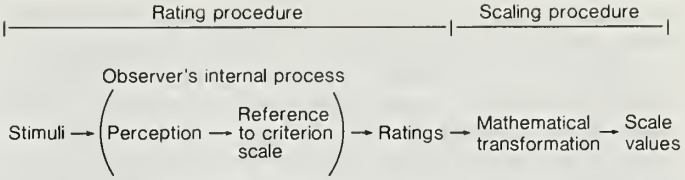

Figure 1.—Conceptual model of the rating and scaling procedures.

The *rating procedure* requires that observers record their ratings of the stimuli on the rating response scale provided. Observers are presented with stimuli and, via an internal perceptual and cognitive process, produce overt ratings. Because the experimental design of the rating exercise delineates the specific characteristics of this procedure, it must be carefully conceived to meet the overall objective of an accurate assessment (vis-a-vis the circumstances to which the results are to be generalized) of the perceived values of the stimuli. The end product of the rating procedure is a matrix of ratings by observers of stimuli. The rating for a given stimulus depends upon both the perceived value of the stimulus (e.g., perceived scenic beauty) and the judgment criterion scale being applied (e.g., how beautiful a scene must be perceived to be to merit a given rating). Thus, the rating recorded by an observer cannot be interpreted as a direct indicator of the perceived value for that stimulus. The purpose of the *scaling procedure* is to apply appropriate mathematical transformations to the ratings so as to produce *scale values* for the stimuli. These scale values are intended to indicate the perceived values of the stimuli, or, more correctly, the relative positions of the stimuli on the psychological dimension being assessed.

Within the rating procedure, a distinction is made between observers' perceptions of a stimulus and their criteria for assigning ratings to the stimulus. This two-part model (Daniel and Boster 1976) follows the psychophysical models developed by Thurstone (Torgerson 1958), as extended by signal detection theory (Green and Swetts 1966). In simplified terms, the model postulates that implicit *perceptual* processes encode the features of the stimulus and translate them into a subjective impression of that stimulus for the dimension being judged (e.g., if the stimulus is an outdoor scene, the dimension could be scenic beauty). This perceptual process is influenced by the features of the stimulus in interaction with the sensory and perceptual system of the observer, and may involve both "cognitive" and "affective" processes (Kaplan 1987, Ulrich 1983, Zajonc 1980). The result of this process is a *relative* impression of the stimulus—of its place relative to other possible stimuli. To produce an overt rating, the perception of the stimulus must be referenced to a *judgment criterion* scale. The organization of that scale allows the perceived value of the stimulus to be expressed, as on a 10-point rating scale.[2]

[2]*Forced-choice (e.g., paired-comparison) and rank-order procedures avoid the criterion component; in these procedures, the observer's response is only dependent on the relative perceived value of each stimulus.*

Figure 2 depicts how hypothetical perceived values for each of three stimuli could produce overt ratings according to four different observers' judgment criterion scales. For this example the perceived values for the three stimuli are assumed to be identical for all four observers, and are indicated by the three horizontal lines that pass from the "perceived value" axis through the four different judgment criterion scales. When referred to the judgment criterion scale of observer A, the perceived value of stimulus 1 is sufficient to meet the criterion for the eighth category, but not high enough to reach the ninth category, so the observer would assign a rating of 8 to the stimulus. Similarly, the same stimulus would be assigned a rating of 10 according to observer C's judgment criterion scale, and only a 6 according to observer D's judgment criterion scale.

The illustration in figure 2 begins with the assumption that the four observers have identical perceptions of the stimuli, but different judgment criterion scales. In actual applications, of course, neither the perceived values nor the criterion scales are known; only the overt ratings are available for analysis. However, guided by a psychometric model, scaling procedures derive estimates of differences in perceived values that are potentially independent of differences in judgment criteria. Relationships between ratings of different stimuli by the same observer(s) are used to infer perceptions. Given the conditions illustrated in figure 2, where only observer rating criteria differ, the ideal scaling procedure would translate each observer's ratings so that the scale values for a given stimulus would be identical for all four observers.

Problems With Interpreting Rating Scales

Unequal-interval judgment criterion scales.—The rating scale provides an opportunity for observers to directly indicate magnitudes of differences in their perceptions of the objects, which is not provided by either paired-comparison or rank-order techniques. However, for this to occur, the intervals between rating categories must be equal with regard to the underlying property being measured. Equally spaced intervals would require that, for example, the difference in the dimension being rated yielding an increase in rating from 2 to 3 is equal to the difference in that dimension yielding an increase in rating from 6 to 7. The criterion scales of observers B, C, and D of figure 2 are equal-interval scales, while the scale of observer A is an unequal-interval scale.

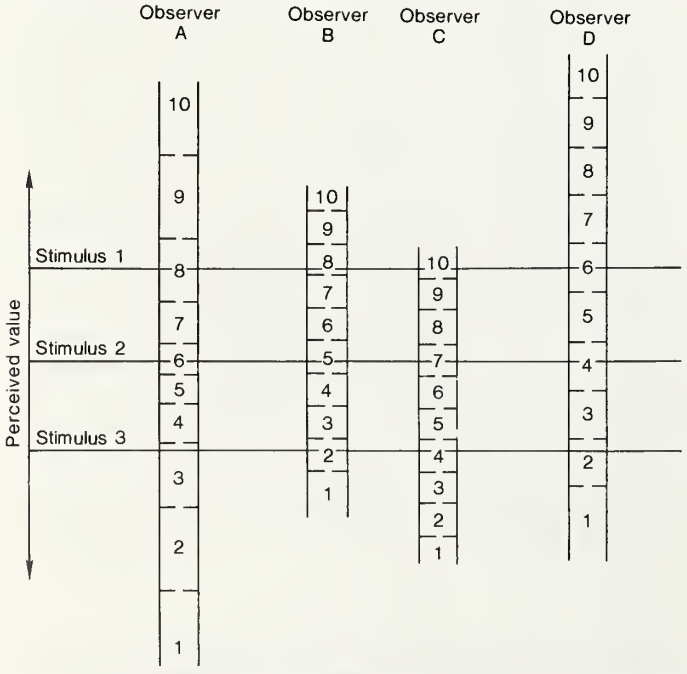

Figure 2.—Judgment criterion scales of four observers with identical perceived values.

Unfortunately, the intervals between rating categories on the underlying psychological dimension will not necessarily be equal. An obvious potential cause of unequal intervals in people's use of the rating scale is the "end-point" problem. This problem could arise when an observer encounters a stimulus to be rated that does not fit within the rating criteria that the observer has established in the course of rating previous stimuli. For example, the observer may encounter a stimulus that he/she perceives to have considerably less of the property being rated than a previous stimulus that was assigned the lowest possible rating. This new stimulus will also be assigned the lowest possible rating, which may result in a greater range of the property being assigned to the lowest rating category than to other rating categories. This may occur at both ends of the rating scale, resulting in a sigmoid type relationship between ratings and the underlying property (Edwards 1957).

The end-point problem can be ameliorated by showing observers a set of "preview" stimuli that depicts the range of stimuli subsequently to be rated. This allows observers to set ("anchor") their rating criteria to encompass the full range of the property to be encountered during the rating session. Hull et al. (1984) used this procedure when they compared rating scale values to paired-comparison scale values for the same stimuli. Paired-comparisons, of course, are not subject to an end-point constriction. The linear relationship they found between the two sets of scale values extended to the ends of the scale, suggesting that the ratings they obtained did not suffer from the end-point problem.

Of course, the end-point problem is not the only potential source of unequal-interval ratings. Observers are free to adopt any standards they wish for assigning their ratings, and there is no a priori reason to expect that they will use equal intervals. For example, the intervals might gradually get larger the farther they are from the center of the scale, as in the criterion scale of observer A in figure 2.

Because it is not possible to directly test for equality of intervals among an observer's ratings, some statisticians argue that ratings should not be used as if they represent interval data (e.g., Golbeck 1986). Others, however, argue, based on Monte Carlo simulations and other approaches, that there is little risk in applying parametric statistics to rating data, especially if ratings from a sufficient number of observers are being combined (Baker et al. 1966, Gregoire and Driver 1987, O'Brien 1979). Nevertheless, the possibility of an unequal-interval scale leaves the level of measurement

achieved by rating scales somewhat ambiguous. The critical issue, of course, is how the ratings, and any statistics or indices computed from those ratings, relate to the underlying (psychological) dimension that is being assessed. This issue can only be addressed in the context of some theory or psychometric model of the perceptual/judgmental process.

Lack of interobserver correspondence.—Individual observer's ratings frequently do not agree with those of other observers for the same stimuli. Lack of correspondence could result from differences in perception, which of course is not a "problem" at all; rather it is simply a finding of the rating exercise at hand. Lack of correspondence could also result from poor understanding of the rating task, poor eyesight or other sensory malfunction, simple observer distraction, or even intentional misrepresentation. Principal component analysis or cluster analysis techniques may be useful to determine whether observers fall into distinct groups with regard to their perception of the stimuli, or whether observers who disagree are unique. In some cases it may be appropriate to either drop some observers from the sample (as being unrepresentative of the population of interest) or weight their ratings less than others.

Most often, lack of correspondence between observers will be due to differences in the judgment (rating) criteria adopted. Even if individual observers each employ equal-interval rating criteria, criterion scales can vary between observers, or the same observer may change criteria from one rating session to another. As a consequence, ratings can differ even though the perception of the stimuli is the same (as shown in fig. 2). When differences between observers' ratings are due only to differences in the criterion scale (i.e., their perceived values are the same), their resulting ratings will be monotonically related, but not necessarily perfectly correlated. But if these observers employ equal-interval criterion scales, the resulting ratings will also be perfectly correlated (except for random variation).

Linear differences in ratings consist of "origin" and "interval size" components. Assuming equal-interval scales, these two components can be estimated for two sets of ratings of the same stimuli by simply regressing one set on the other. The intercept and slope coefficients of the regression would indicate the origin and interval size differences, respectively. As an example of an origin difference, consider criterion scales of observers B and C in figure 2. Remember that all observers in figure 2 are assumed to agree in their *perception* of the stimuli. Observer B's and C's criterion scales have identical interval sizes, but B's scale is shifted up two rating values compared with C's scale (suggesting that observer B adopted more stringent criteria, setting higher standards than observer C). The ratings of these two observers for scenes 1, 2, and 3 can be made identical by a simple origin shift—either adding "2" to each of B's ratings or subtracting "2" from each of C's ratings.

Observers' criterion scales can probably be expected to differ somewhat by both their origin and interval size. As an example, consider the criterion scales of observers C and D in figure 2. The judgments for the three stimuli (ratings of 4, 7, and 10 for observer C and 2, 4, and 6 for observer D) indicate that these scales differ by an origin shift of 1.0 and an interval size of 1.5. That is, the relationship between the ratings of observers C and D is represented by $R_C = 1 + 1.5\ R_D$, where R_C and R_D indicate the ratings of observers C and D, respectively.

There is no direct way to observe either the perceived values of the stimuli or the judgment criteria used by the observer; both are implicit psychological processes. Thus, if two sets of ratings are linearly related, it is impossible to tell for sure whether the ratings were produced (1) by two observers who have identical rating criterion scales, but perceive the stimuli differently; (2) by two observers who perceive the stimuli the same, but use different criterion scales; or (3) by two observers who differ both in perception and rating criteria. In our application of the basic psychometric model, however, we have taken the position that perception is a relatively consistent process that is strongly related to the features of the stimulus, while judgment (rating) criteria are more susceptible to the effects of personal, social, and situational factors. This is a theoretical position that is consistent with the Thurstone and signal detection theory models (Brown and Daniel 1987, Daniel and Boster 1976, Hays 1969). Given this position, linear differences (i.e., differences in origin and interval size) between sets of ratings are generally taken to be indications of differences in judgment criteria, not differences in perception. When differences in ratings are due to the criterion scales used by different observers (or observer groups), psychometric scaling procedures can adjust for these effects and provide "truer" estimates of the perceived values of the stimuli.

Linear differences between group average criterion scales.—A related problem may arise where ratings of two different observer groups are to be compared. The two groups may on average use different rating criteria, perhaps because of situational factors such as when the rating sessions of the different groups occurred. For example, time of day may influence ratings, regardless of the specific attributes of the stimuli being judged. Scaling procedures can be used to adjust for criterion differences (origin and interval) between observer groups.

Lack of intraobserver consistency.—An individual observer's ratings can be inconsistent, with different ratings being assigned to the same stimulus at different times. This problem is not restricted to ratings, but can occur whenever an observer's perception and/or rating criterion boundaries waver during the rating exercise, so that, for example, a given stimulus falls in the "6" category on one occasion and in the "5" category the next.

Psychometric models generally assume that both the perceived values and the judgment criteria will vary somewhat from moment to moment for any given stimulus/observer. This variation is assumed to occur because of random (error) factors, and thus is expected to yield a normal distribution of perceived criterion values centered around the "true" values (Torgerson 1958). Given these assumptions, the mean of the resulting ratings for a stimulus indicates the "true value" for that stimulus,

and the variance of the observer's ratings for that stimulus indicates the variation in underlying perceived values combined with variation in rating criterion boundaries. The effects of inconsistencies in an observer's ratings can be ameliorated by obtaining a sufficient number of judgments of each stimulus (by requiring each observer to judge each stimulus several times) to achieve a stable estimate of the perceived values. Repeated presentation of the same stimuli may, however, lead to other problems.

Perceptual and criterion shifts.—In some circumstances there may be a *systematic* shift in rating criteria and/or perception over the course of a rating session. Such a shift could be related to the order in which the stimuli are presented, or to other aspects of the rating session.[3] This is a potential problem with all types of observer judgments where several stimuli are judged by each observer. If the problem is related to order of presentation, it can be controlled for by presenting the stimuli to different observers (or on different occasions) in different random orders. If the shift is primarily due to changing criteria, it may be possible to adjust for this effect to reveal more consistent perceived values.

Baseline Adjustments

It is often necessary to combine the ratings for a set of stimuli obtained in one rating session with ratings for another set of stimuli obtained in a different rating session (for examples, see Brown and Daniel (1984) and Daniel and Boster (1976)). This need may occur, for example, when ratings are needed for a large group of stimuli that cannot all be rated in the same session. In such cases, the investigator's option is to divide the set of stimuli into smaller sets to be rated by different observer groups, or by the same group in separate sessions. In either case, it is important that some stimuli are common to the separate groups/sessions; this provides a basis for determining the comparability of the ratings obtained from the different groups/sessions, and possibly a vehicle to "bridge the gap" between different groups/sessions. The subset of stimuli common to all rating sessions is called the *baseline*.

If baseline stimuli are to be used to determine comparability between two or more rating sessions, it is important that the baseline stimuli be rated under the same circumstances in each case. Otherwise, the ratings may be influenced by unwanted experimental artifacts, such as interactions between the baseline stimuli and the other stimuli that are unique to each session. To enhance the utility of baseline stimuli, the following precautions should be followed: (1) the observers for each session should be randomly selected from the same observer population, (2) the observer groups should be sufficiently large, (3) the baseline stimuli should be representative of the full set of stimuli to be rated, (4) the other (nonbaseline) stimuli should be randomly assigned to the different sessions,[4] and (5) all other aspects of the sessions (e.g., time of day, experimentor) should remain constant.

The effectiveness of a baseline is also a function of the number of stimuli included in the baseline. The greater the proportion of the stimuli to be rated that are baseline stimuli, the more likely that the baseline will adequately pick up differences in use of the rating scale between observers or observer groups, all else being equal. Of course, one must trade off effectiveness of the baseline with the decrease in the number of unique stimuli that can be rated in each session as the baseline becomes larger.

If proper experimental precautions are followed, it is unlikely that the ratings will reflect substantial perceptual differences among the different groups/sessions. In this case, given the model described above, we would assume that any differences across sessions in baseline ratings were due to differences in judgment criteria, not differences in perception, and we would then proceed to use the baseline ratings to "bridge the gap" between the rating sessions.

In the following section, we describe and compare 11 methods for scaling rating data. Some of these procedures attempt to compensate or adjust for the potential problems described above, and some utilize a baseline. We do not attempt to determine the relative merit of these procedures. Our purpose is to provide the reader with the means to evaluate the utility of the various scaling procedures for any given application.

SCALING PROCEDURES

Eleven scaling procedures are described, from the simple median and mean to the more complex Scenic Beauty Estimation (SBE) and least squares techniques. All 11 procedures are provided by RMRATE (Brown et al. 1990). All but one of the scaling procedures provide a scale value for each stimulus, and all procedures provide scale values for groups of stimuli. In addition, some of the procedures provide scale values for each rating. The scaling options are described below, along with some discussion of the relative advantages and disadvantages of each.

Differences among the various scaling methods are illustrated using several sets of hypothetical rating data. Each set of data represents ratings of the same five stimuli by different groups of observers. For example, table 1 presents the ratings of three hypothetical observer groups (A, B, and C) each rating the same five stimuli

[3] *An example of such shifts is found in the "context" study reported by Brown and Daniel (1987). Two observer groups each rated the scenic beauty of a set of common landscape scenes after they had rated a set of unique (to the groups) scenes. Because of the differences between the two sets of unique scenes, the ratings of the initial common scenes were quite different between the groups. However, as more common scenes were rated, the groups' ratings gradually shifted toward consensus.*

[4] *An example of where this guideline was not followed is reported by Brown and Daniel (1987), where mean scenic beauty ratings for a constant set of landscape scenes were significantly different depending upon the relative scenic beauty of other scenes presented along with the constant (baseline) scenes. In that study, the experimental design was tailored precisely to encourage, not avoid, differences in rating criteria by different observer groups.*

(1, 2, 3, 4, and 5). Table 1 provides a comparison of simple mean ratings and baseline-adjusted mean ratings as scaling options. Subsequent tables use some of the same rating sets (observer groups), as well as additional hypothetical groups, to compare the other scaling options. Additional comparisons of the scaling procedures are presented in the appendix.

Median Rating

The scale value calculated using this procedure represents the numerical rating that is above the ratings assigned by one-half of the observers and below the ratings assigned by the other half of the observers. Thus, the median is simply the midpoint rating in the set of ordered ratings; e.g., among the ratings 3, 6, and 2, the median is 3. If there is an even number of observers, the median is the average of the two midpoint ratings; e.g., among the ratings 2, 4, 5, and 6, the median is 4.5. If the ratings assigned to a stimulus are symmetrically (e.g., normally) distributed, the median is equal to the mean rating.

An advantage of the median is that it does not require the assumption of equal-interval ratings. The corresponding disadvantage is that it provides only an ordinal (rank-order) scaling. In terms of the psychological model presented above, selecting the median ratings as the scale value restricts one to simple ordinal (greater than, less than) information about the position of stimuli on the underlying psychological dimension (e.g., perceived beauty).

Mean Rating

In many applications researchers have used simple average ratings as a scale value. The mean rating for a stimulus is computed as:

$$MR_i = \frac{1}{n} \sum_{j=1}^{n} R_{ij} \qquad [1]$$

where

MR_i = mean rating assigned to stimulus i
R_{ij} = rating given to stimulus i by observer j
n = number of observers.

Table 1 lists ratings by three hypothetical observer groups that each rated 5 stimuli. The mean rating for each stimulus within each data set is also listed.

Ratings, and mean ratings, do provide some indication of the magnitude of differences between objects, representing an improvement over ranks in the direction of an interval measure. However, simply averaging rating scale responses is potentially hazardous, as it requires the assumption that the intervals between points on the rating scale are equal. Some statisticians are very reluctant to allow this assumption, and reject the use of average ratings as a valid measure of differences in the underlying property of the objects being measured. Other statisticians are more willing to allow the use of mean ratings, at least under specified conditions. The results of computer modeling studies support the latter position. These studies have shown that when ratings are averaged over reasonable numbers of observers (generally from about 15 to 30) who rate the same set of objects, the resulting scale values are very robust to a wide range of interval configurations in the individual rating scales (see citations in the Psychological Scaling section, above, plus numerous papers in Kirk (1972)).

To compare mean ratings of stimuli judged during a given session, one must assume that on average the rating criterion scale is equal interval. A group's rating criterion scale is equal interval "on average" (1) if each observer used an equal-interval rating criterion scale, or (2) if the deviations from equal intervals employed by specific observers are randomly distributed among ob-

Table 1.—Ratings and origin-adjusted ratings (OARs) for three observer groups.

		Rating			OAR			Scale value	
	Observer. . .	1	2	3	1	2	3		
Observer group	Stimulus							Mean rating	Mean OAR
A	1	1	3	6	−2.0	−2.0	−2.0	3.33	−2.00
	2	2	4	7	−1.0	−1.0	−1.0	4.33	−1.00
	3	3	5	8	.0	.0	.0	5.33	.00
	4	4	6	9	1.0	1.0	1.0	6.33	1.00
	5	5	7	10	2.0	2.0	2.0	7.33	2.00
B	1	1	2	1	−4.0	−4.0	−4.0	1.33	−4.00
	2	3	4	3	−2.0	−2.0	−2.0	3.33	−2.00
	3	5	6	5	.0	.0	.0	5.33	.00
	4	7	8	7	2.0	2.0	2.0	7.33	2.00
	5	9	10	9	4.0	4.0	4.0	9.33	4.00
C	1	1	2	2	−4.0	−4.0	−4.0	1.67	−4.00
	2	3	4	4	−2.0	−2.0	−2.0	3.67	−2.00
	3	5	6	6	.0	.0	.0	5.67	.00
	4	7	8	8	2.0	2.0	2.0	7.67	2.00
	5	9	10	10	4.0	4.0	4.0	9.67	4.00

servers (there are no consistent deviations, such as all or most observers compressing the end-points of the scale). The assumption of equal-interval criterion scales is probably never strictly met for individual observers, but for sufficiently large groups of observers (15 to 30 or more, depending on variability within the group) it may not be unreasonable to assume that "on average" the intervals between categories are approximately equal.

The experimentor must decide whether and when it is appropriate to use mean ratings as an index of preference, quality, or whatever property is being measured. In typical applications with multiple observers and a proper experimental design, however, we have rarely found situations in which the results of using mean ratings, as compared to more sophisticated scaling methods, produced substantive differences in conclusions, statistical or scientific, regarding relative preferences or perceived quality (see also Schroeder (1984)). However, use of mean ratings as interval scale data must be approached with considerable caution. In the final analysis, differences between mean ratings will assuredly indicate commensurate differences on the underlying psychological dimension only if the rating criterion scales of relevant observers or groups are equal-interval.

Origin-Adjusted Rating

This procedure applies an origin adjustment to each observer's ratings prior to aggregating over observers to obtain a group index for a stimulus. First, individual observer's ratings are transformed to origin-adjusted ratings (OARs) by subtracting each observer's mean rating from each of his or her ratings as follows:

$$OAR_{ij} = R_{ij} - MR_j \quad [2]$$

where

OAR_{ij} = origin-adjusted rating of stimulus i by observer j
R_{ij} = rating assigned to stimulus i by observer j
MR_j = mean rating assigned to all stimuli by observer j.

Then the OAR_{ij} are averaged across observers in a group, in a similar fashion to the averaging of raw ratings in equation [1], to give one scale value for each stimulus.

OARs of three hypothetical observer groups are listed in table 1. The ratings of the three observers of group A have the same interval size (the difference in ratings between any two stimuli is the same for all observers) but different origins (the mean ratings of the observers differ). Thus, when the mean rating of each observer is subtracted from each of the observer's ratings, the resulting OARs of all three observers are identical for any given stimulus. That is, the adjustment has removed the origin differences among observers to reveal, assuming common perception, that the observers do not differ in how they distinguish the relative differences among stimuli. Similarly, the OARs of observers in groups B and C are identical, and the mean OARs of the two sets are identical.

Baseline-Adjusted OAR

When scale values are needed for large numbers of stimuli, requiring two or more separate rating groups or sessions, use of a common set of stimuli, a *baseline* as described above, is recommended. In such situations, a variation of the OAR technique may be applied, whereby the origin adjustment is accomplished by subtracting the mean of the baseline stimuli (rather than the mean of all stimuli) from each rating. This baseline-adjusted OAR is computed by:

$$BOAR_{ij} = R_{ij} - BMR_j \quad [3]$$

where

$BOAR_{ij}$ = baseline-adjusted OAR of stimulus i by observer j
R_{ij} = rating assigned to stimulus i by observer j
BMR_j = mean rating assigned to baseline stimuli by observer j.

The $BOAR_{ij}$ are then averaged across observers in a group or session to yield one scale value for each stimulus. Of course, the cautions regarding the proper design of the baseline "bridges" between different rating groups/sessions should be carefully considered.

The origin-adjustment corrects for the effects of differences in the origin of observers' rating criterion scales, but not for the effects of differences in interval size, as seen by comparing ratings of group A with those of groups B and C in table 1. Mean OARs are identical for groups B and C, which each used an interval of two rating points for distinguishing between proximate stimuli. Group A, however, exhibits an interval size of only 1, resulting in mean OARs that differ from those of the other two groups. A more sophisticated standardized score, such as the Z-score presented next, adjusts for both origin and interval differences and, thus, is preferable to a simple origin adjustment. However, the origin-adjusted rating is included here to facilitate the transition from simple mean ratings to more sophisticated standardized scores. If an investigator is willing to assume that observers/groups differ *only* in the origin of their rating criteria, then origin-adjusted ratings could be taken as indicators of stimulus locations on the underlying (hypothetical) scale.

Z-Score

This procedure employs a Z-score transformation of individual observer's ratings prior to aggregating over observers to obtain a group index for a stimulus. First, individual observer's ratings are transformed to *standard* scores using the conventional formula:

$$Z_{ij} = (R_{ij} - MR_j) / SDR_j \quad [4]$$

where

Z_{ij} = Z-score for stimulus i by observer j
R_{ij} = rating assigned to stimulus i by observer j
MR_j = mean rating assigned to all stimuli by observer j

SDR_j = standard deviation of ratings assigned by observer j
n = number of observers.

Then the Z_{ij} are averaged across observers in the group to give one scale value for each stimulus.

Z-scores have several important characteristics. For each individual observer, the mean of the Z-scores over the stimuli rated will always be zero. Also, the standard deviation of the Z-scores for each observer will always be 1.0. Thus, the initial ratings assigned by an observer, which may be affected by individual tendencies in use of the rating scale, are transformed to a common scale that can be directly compared between (and combined over) observers. Note that this procedure allows direct comparison even if different observers used explicitly different rating scales, such as a 6-point scale versus a 10-point scale.

When Z-scores are computed for individual observers by [4], the mean and standard deviation of the resulting scale will be changed to 0 and 1.0, respectively. The *shape* of the resulting Z-score distribution, however, will be the same as that of the original rating distribution, because only a linear transformation of the ratings has been applied (e.g., it will not be forced into a normal distribution). However, the subsequent procedures of averaging individual observer Z-scores to obtain aggregate (group) indices for stimuli makes individual departures from normality relatively inconsequential.[5]

The transformation effected by the Z-score computation removes linear difference among observers' ratings. All differences among observers' ratings that result from criterion scale differences will be linear if the observers employed equal-interval criterion scales. Thus, to the extent that observers' criterion scales were equal-interval, arbitrary differences between observers in how they use the rating scale are removed with the Z transformation. These differences include both the tendency to use the high or low end of the scale (origin differences) and differences in the extent or range of the scale used (interval size differences), as illustrated in figure 2. If the equal-interval scale assumption is satisfied, scaling ratings by the Z transformation allows any differences among the observers' Z-scores to reflect differences in the perceived values of the stimuli.

Hypothetical ratings and corresponding Z-scores are listed in table 2 for four observer groups. Three results of the Z-score transformation can be seen in table 2. First, the Z-score transformation adjusts for origin differences, as can be seen by comparing ratings and Z-scores among observers of group A, or among observers of group B. Second, the transformation adjusts for interval size differences, as can be seen by comparing ratings and Z-scores of observer 2 of group A with those of observer 1 of group B. The combined effect of these two adjustments is seen by examining group E, which includes a mixture of ratings from groups A and B. Finally, it is seen by comparing groups B and D that sets of ratings that produce identical mean ratings do not necessarily produce identical mean Z-scores. Two sets of ratings will necessarily produce identical mean Z-scores only if the sets of ratings are perfectly correlated (if the ratings of each observer of one set are linearly related to all other observers of that set and to all observers of the other set).

[5]*The basis for this claim is the same as that which supports the application of normal distribution ("parametric") statistics to data that are not normally distributed.*

Table 2.—Ratings and Z-scores for four observer groups.

		Rating			Z-score			Scale value	
	Observer. . .	1	2	3	1	2	3		
Observer group	Stimulus							Mean rating	Mean Z-score
A	1	1	3	6	−1.26	−1.26	−1.26	3.33	−1.26
	2	2	4	7	−.63	−.63	−.63	4.33	−.63
	3	3	5	8	.00	.00	.00	5.33	.00
	4	4	6	9	.63	.63	.63	6.33	.63
	5	5	7	10	1.26	1.26	1.26	7.33	1.26
B	1	1	2	1	−1.26	−1.26	−1.26	1.33	−1.26
	2	3	4	3	−.63	−.63	−.63	3.33	−.63
	3	5	6	5	.00	.00	.00	5.33	.00
	4	7	8	7	.63	.63	.63	7.33	.63
	5	9	10	9	1.26	1.26	1.26	9.33	1.26
D	1	1	2	1	−.95	−1.63	−1.14	1.33	−1.24
	2	2	6	2	−.63	−.15	−.89	3.33	−.56
	3	3	7	6	−.32	.22	.10	5.33	.00
	4	5	8	9	.32	.59	.84	7.33	.58
	5	9	9	10	1.58	.96	1.09	9.33	1.21
E	1	1	6	1	−1.26	−1.26	−1.26	2.67	−1.26
	2	2	7	3	−.63	−.63	−.63	4.00	−.63
	3	3	8	5	.00	.00	.00	5.33	.00
	4	4	9	7	.63	.63	.63	6.67	.63
	5	5	10	9	1.26	1.26	1.26	8.00	1.26

Baseline-Adjusted Z-Score

When different observers have rated sets of stimuli that only partially overlap, and their scores are to be compared, baseline stimuli can provide a common basis for transforming individual observer's ratings into a standardized scale. Using ratings of the baseline stimuli as the basis of the standardization, the baseline-adjusted Z-score procedure computes standard scores as:

$$BZ_{ij} = (R_{ij} - BMR_j) / BSDR_j \quad [5]$$

where

BZ_{ij} = baseline-adjusted standard score of stimulus i for observer j
R_{ij} = rating of stimulus i by observer j
BMR_j = mean rating of the baseline stimuli by observer j
$BSDR_j$ = standard deviation of ratings of the baseline stimuli by observer j.

The BZ_{ij} are then averaged across observers to yield one scale value per stimulus (BZ_i).

All ratings assigned by an observer are transformed by adjusting the origin and interval to the mean and standard deviation of that observer's ratings of the baseline stimuli. BZ, then, is a standardized score based only on the stimuli that were rated in common by all observers in a given assessment. While the standardization parameters (mean and standard deviation) are derived only from the baseline stimuli, they are applied to all stimuli rated by the observer. Thus, as stated above, it is important that the baseline stimuli be reasonably representative of the total assessment set, and that the additional "nonbaseline" stimuli rated by the separate groups (sessions) are comparable.

Given the assumptions described above, the computed-Z procedures transform each observer's ratings to a scale that is directly comparable to (and can be combined with) the scale values of other observers. This is accomplished by individually setting the origin of each observer's scale to the mean of the ratings that observer assigned to all of the stimuli (or the baseline stimuli). The interval, by which differences between stimuli are gauged, is also adjusted to be the standard deviation of the observer's ratings of all (or the baseline) stimuli. The appropriate scale value for each stimulus is the mean Z over all observers.[6]

The Z transformation is accomplished individually for each observer, without reference to the ratings assigned by other observers. An alternative procedure is to select origin and interval parameters for each observer's scale so that the best fit is achieved with the ratings assigned by all of the observers that have rated the same stimuli. This "best fit" is achieved by the least squares procedure described next.

[6]*Both origin and interval are arbitrary for interval scale measures. The origin for the mean Z-score scale (the zero point) will be the grand mean for all stimuli (or all baseline stimuli), and the interval size for the scale will be 1.0 divided by the square root of the number of observers. Because the interval size depends on the number of observers, one must be careful in making absolute comparions between mean Zs based on different sized observer groups. This would not, however, affect relative comparisons (e.g., correlations) between groups.*

Least Squares Rating

This procedure is based on a least squares analysis that individually "fits" each observer's ratings to the mean ratings of the entire group of observers. There are two variants of the procedure, depending upon whether ratings of all stimuli, or only the baseline stimuli, are used to standardize or fit the individual observer's ratings.

Part of the rationale for transforming observers' ratings to some other scale is that the ratings do not directly reflect the associated values on the assumed psychological dimension that is being measured. The need for transformation is most obvious when different observers rate the same objects using explicitly different rating scales; unstandardized ratings from a 5-point scale cannot be directly compared or combined with ratings from a 10-point scale, and neither can be assumed to directly reflect either the locations of, or distances between, objects on the implicit psychological scale. Similarly, even when the same explicit rating scale is used to indicate values on the psychological dimension, there is no guarantee that every observer will use that scale in the same way (i.e., will use identical rating criteria).

The goal of psychological scaling procedures is to transform the overt indicator responses (ratings) into a common scale that accurately represents the distribution of values on the psychological dimension that is the target of the measurement effort. The Z-score procedure approaches this measurement problem by individually transforming each observers's ratings to achieve a standardized measure for each stimulus. Individual observer's ratings are scaled independently (only with respect to that particular observer's rating distribution) and then averaged to produce a group index for each stimulus. The least squares procedure, like the Z-score procedure, derives a scale value for each observer for each stimulus. Individual observer's actual ratings, however, are used to estimate ("predict") scores for each stimulus based on the linear fit with the distribution of ratings assigned by the entire group of observers that rated the same stimuli. This estimated score is produced by regressing the group mean ratings for the stimuli (MR_i) on the individual stimulus ratings assigned by each observer (R_{ij}). The resulting regression coefficients are then used to produce the estimated ratings:

$$LSR_{ij} = a_j + b_j R_{ij} \quad [6]$$

where

LSR_{ij} = least squares rating for stimulus i of observer j
R_{ij} = raw rating for stimulus i assigned by observer j
a_j = intercept of the regression line for observer j
b_j = slope of the regression line for observer j.

This is done for each observer, so that a LSR_{ij} is estimated for each R_{ij}.

Table 3 lists ratings and associated least squares scores for six observer groups. The table shows that if the rat-

Table 3.—Ratings and least squares ratings for six observer groups.

Observer group	Stimulus	Rating 1	Rating 2	Rating 3	LSR 1	LSR 2	LSR 3	Scale value: Mean rating	Scale value: Mean LSR
A	1	1	3	6	3.33	3.33	3.33	3.33	3.33
	2	2	4	7	4.33	4.33	4.33	4.33	4.33
	3	3	5	8	5.33	5.33	5.33	5.33	5.33
	4	4	6	9	6.33	6.33	6.33	6.33	6.33
	5	5	7	10	7.33	7.33	7.33	7.33	7.33
B	1	1	2	1	1.33	1.33	1.33	1.33	1.33
	2	3	4	3	3.33	3.33	3.33	3.33	3.33
	3	5	6	5	5.33	5.33	5.33	5.33	5.33
	4	7	8	7	7.33	7.33	7.33	7.33	7.33
	5	9	10	9	9.33	9.33	9.33	9.33	9.33
D	1	1	2	1	2.48	.51	1.81	1.33	1.60
	2	2	6	2	3.43	4.89	2.57	3.33	3.63
	3	3	7	6	4.38	5.99	5.64	5.33	5.34
	4	5	8	9	6.28	7.09	7.94	7.33	7.10
	5	9	9	10	10.08	8.18	8.71	9.33	8.99
E	1	1	6	1	2.67	2.67	2.67	2.67	2.67
	2	2	7	3	4.00	4.00	4.00	4.00	4.00
	3	3	8	5	5.33	5.33	5.33	5.33	5.33
	4	4	9	7	6.67	6.67	6.67	6.67	6.67
	5	5	10	9	8.00	8.00	8.00	8.00	8.00
F	1	1	2	1	1.07	1.07	2.10	1.33	1.41
	2	3	4	2	3.03	3.03	3.07	3.00	3.04
	3	5	6	3	5.00	5.00	4.03	4.67	4.68
	4	7	8	5	6.97	6.97	5.97	6.67	6.63
	5	9	10	9	8.93	8.93	9.83	9.33	9.23
G	1	1	3	3	2.60	2.60	3.36	2.33	2.85
	2	2	4	4	3.07	3.07	2.92	3.33	3.02
	3	3	5	3	3.53	3.53	3.36	3.67	3.48
	4	4	6	2	4.00	4.00	3.79	4.00	3.93
	5	5	7	1	4.47	4.47	4.23	4.33	4.39

ings of two observers in a given group correlate perfectly, they will yield identical LSRs. For example, the ratings by all observers of group A are perfectly correlated and, thus, all observers have identical LSRs. The same is true for observers in groups B and E, and for observers 1 and 2 of group F. However, unlike the Z-score procedure, observers of two different data sets will not necessarily yield identical LSRs, even though their ratings are perfectly correlated or even identical (compare LSRs of observer 1 of groups A, E, and G).

Table 3 also shows that if ratings of all observers within a group are perfectly correlated with each other, as in groups A, B, and E, the group mean LSRs for the stimuli will be identical to the group's mean ratings. However, if ratings of one or more observers in the set are not perfectly correlated with those of other observers, the mean LSRs will not (except by chance) be identical to the mean ratings, as in group F. Finally, it can be seen, by comparing groups B and D, that identical mean ratings will not necessarily produce identical mean LSRs.

The LSR transformation reflects an assumption of the general psychometric model that consistent differences between observers (over a constant set of stimuli) are due to differences in rating criteria, and that consistent differences between stimuli (over a set of observers) indicate differences on the underlying psychological dimension. In the LSR procedure, individual observer's ratings are weighted by the correlation with the group means. The group means are taken to be the best estimate of the "true" values for the stimuli on the underlying perceptual dimension.

Equation [6] can be restated to better reveal how individual observer's estimated ratings are derived from the mean ratings of all observers:

$$LSR_{ij} = MMR + r_{jn} (SDMR/SDR_j) (R_{ij} - MR_j) \quad [7]$$

where

LSR_{ij} = transformed rating scale value for stimulus i for observer j (as above)

MMR = mean of the mean ratings assigned to all stimuli by all observers in the group (the grand mean)

r_{jn} = correlation between observer j's ratings and the mean ratings assigned by all (n) observers in the group

SDMR = standard deviation of the mean ratings assigned by all observers in the group

SDR_j = standard deviation of observer j's ratings

R_{ij} = rating assigned to stimulus i by observer j
MR_j = mean of all ratings by observer j.

As examination of [7] shows, the resulting LSR values for every observer will have a mean (over all stimuli) equal to the grand mean (MMR). The standard deviation of the transformed scale depends upon the correlation between the individual and group mean ratings and on the ratio of the individual and group standard deviations. As in all regression procedures, the standard deviation will be less than or equal to that for the original ratings.

The variation in each individual observer's least squares scale (LSR_{ij}) about the group's grand mean rating (MMR) depends largely on how well the observer agreed with the group of observers (r_{jn}). The greater the absolute value of the correlation, the greater the variation in the observer's LSRs will be. If $r_{jn} = 0$, for example, observer j will contribute nothing toward distinctions among the stimuli. In effect, the least squares procedure weights the contribution of each observer to the group scale values by the observer's correspondence with the group. Thus, in table 3, observers of groups A and B contribute equally to the scale values of their respective data sets, but observers of group D do not. Of particular interest is observer group F. The raw ratings of all three observers have the same range (8) and standard deviation ($SDR_j = 3.16$), but the correlation of an observer's ratings with the group mean ratings (r_{jn}) is slightly larger for observers 1 and 2 (0.995) than it is for observer 3 (0.977). This difference in correlations causes the range and standard deviation of observer 3's LSRs to be smaller than those of observers 1 and 2.

The ratio of standard deviations in [7] ($SDMR/SDR_j$) acts to mediate for differences among observers in the variety (e.g., range) of rating values used over the set of stimuli. Observers who use a relatively large range of the rating scale, and therefore generate relatively large differences between individual ratings and their mean ratings ($R_{ij} - MR_j$), will tend to have larger standard deviations (SDR_j) and, therefore, smaller ratios of standard deviations ($SDMR/SDR_j$), thereby reducing the variation in the observer's LSRs. Conversely, the variance of the LSRs of observers who use a relatively small range of the rating scale will tend to be enhanced by the ratio of standard deviations in [7]. For an example, consider observer group E in table 3. The ratings of all three observers correlate perfectly, so r_{jn} plays no role in distinguishing among the observers' LSR_{ij}. However, the standard deviation of observer 3's ratings is larger than that for observers 1 and 2. It is this difference in SDR_j that adjusts for the difference in interval size in the ratings, causing the three observers' LSRs to be identical.

Observer group G of table 3 contains one observer (number 3) whose ratings correlate negatively (–0.65) with the group mean ratings. The effect of the least squares procedure is to produce LSRs for observer 3 that correlate positively (0.65) with the group mean ratings. The cause of this sign reversal can be seen in [7], where the sign of r_{jn} interacts with the sign of $(R_{ij} - MR_j)$ to reverse the direction of the scores of an observer in serious disagreement with the group (such a person will have a negative r_{jn} and tend to have a sign for $(R_{ij} - MR_j)$ that is contrary to the sign for observers in agreement with the group). This reversal is of small consequence for values of r_{jn} close to 0. But for more substantial negative values of r_{jn}, the reversal is significant, for it in effect nullifies the influence on the group metric of an observer who may actually have "opposite" preferences from the group. If such a reversal is not desired, the observer's ratings should be removed. However, a substantial negative correlation with the group can also arise when the observer has misinterpreted the direction of the rating scale (e.g., taking "1" to be "best" and "10" to be "worst," when the instructions indicated the opposite). If misinterpretation of the direction of the scale can be confirmed, a transformation that reverses the observer's scale, such as that provided by the LSR, would be appropriate.

Baseline-Adjusted LSR

The "baseline" variant of the least squares procedure is the same as the normal least squares procedure described above, but the regression is based only on the fit between the individual and the group for the baseline stimuli. Note that the baseline-adjusted LSR (BLSR) procedure does not provide a mechanism for absolute comparisons of LSRs across observer groups, because the procedure does not adjust for linear, or any other, differences *between* groups; the function of the regression procedure is to weight observers' ratings, not assist comparability across groups.

Comparison of Z-Scores and LSRs

The least squares procedures are related to the Z-score procedures. Both involve a transformation of each individual observer's ratings to another common measurement scale before individual indices are averaged to obtain the group index, and both rely on the assumption of equal interval ratings. The Z-score computation transforms each individual rating distribution to a scale with a mean of 0 and a standard deviation of 1.0. With only a slight modification in the transformation equation, the rating scales could instead be transformed to some other common scale, such as a scale with a mean of 100 and a standard deviation of 10. In any case, the resulting Z-scores for any individual observer are a linear transformation of the observer's initial ratings and, therefore, will correlate perfectly with the observer's initial ratings.

The least squares procedure also transforms each observer's ratings to a common scale, this time based on the group mean ratings. The mean of the least-squares transformed scale for every individual observer is the grand mean rating over all observers, and the standard deviation will depend upon the standard deviation of the original ratings and on the obtained correlation between the individual's ratings and the group average ratings. Like the Z-score procedure, however, an individual

observer's LSRs will correlate perfectly with the observer's initial ratings.

The relationship between the computed Z-score approach and the least squares estimation procedure can be more easily seen by rearranging the terms of the basic regression equation [7] into:

$$(LSR_{ij} - MMR)/SDMR = r_{jn} (R_{ij} - MR_j)/SDR_j \quad [8]$$

In this arrangement the left term is recognized as $Z_{LSR_{ij}}$, the standardized transform of the least squares estimated ratings of observer j. The right term includes the correlation between observer j's ratings of the stimuli and the mean ratings assigned by the group, r_{jn}, and the standardized form of the observer's ratings, Z_{ij} (see [4]). Note that if $|r_{jn}| = 1.0$ (indicating a perfect linear relationship between observer j's ratings and the group mean ratings), $Z_{LSR_{ij}}$ and Z_{ij} are equal. For this to occur, the observer's ratings and the group mean ratings would have to differ only by a linear transform; i.e., they would have to be equal except for their origin and interval size, which are arbitrary for equal-interval scales. Because $|r_{jn}|$ is virtually never 1.0, the computed Z-scores (Z_{ij}) will not generally be equal to the $Z_{LSR_{ij}}$, and neither will be equal to the standardized group means. However, unless the individual observer correlations with the group means differ substantially, the distributions of average scale values, the mean Z_i and the mean LSR_i, will be strongly correlated.

Unlike the computed Z scale, which is a standardized scale, the least squares estimated scale is always in terms of the original rating scale applied; i.e., a 10-point scale will produce transformed scores that can only be compared to other scales based on 10-point ratings. This may be an advantage for communication of the rating results; for example, it avoids the negative number aspect of the Z-score scale. At the same time, care must be exercised in combining or comparing one least squares scale with others, especially if the other scales are based on a different explicit rating scale. This comparability problem can be overcome, however, by appropriate transformations of the final scale (as to percentiles, Z-scores, or some other "standard" distribution).

Scenic Beauty Estimate

Scenic Beauty Estimate (SBE) scaling procedures were originally developed for use in scaling ratings of scenic beauty of forest areas (Daniel and Boster 1976), but the procedures are appropriate for use with ratings of other types of stimuli. Both the "by-observer" and "by-slide" options for deriving SBEs proposed by Daniel and Boster (1976) are described here. The derivation of individual scale values in each option follows Thurstone's "Law of Categorical Judgment" (Torgerson 1958), modified by procedures suggested by the "Theory of Signal Detectability" (Green and Swetts 1966). Scale values are derived from the overlap ("confusion") of the rating distributions of different stimuli, where the rating distributions are based on multiple ratings for each stimulus. The overlap in stimulus rating distributions indicates the proximity of the stimuli on the underlying psychological dimension (e.g., perceived beauty). SBEs provide an equal-interval scale measure of perceived values, given the underlying measurement theory and computational procedures, as described by Hull et al. (1984).

Following the general psychometric model introduced earlier, the rating assigned to a stimulus indicates the relationship between the perceived value of the stimulus and the categories on the observer's rating criterion scale being applied on that occasion. For a stimulus to be rated an "8", its perceived value must be below the upper boundary of the "8" category on the criterion scale, but above the upper boundary for a rating of "7" (as illustrated by observer A for stimulus 1 in fig. 2). Thurstone's Law of Categorical Judgment proposes that the magnitude of the difference between the perceived value of a stimulus and the location of the lower boundary of a given rating category (e.g., for an "8") can be represented by the unit normal deviate corresponding to the proportion of times that the stimulus is perceived to be above that criterion category boundary.[7]

As Torgerson (1958) explains, the Law of Categorical Judgment relies on variation in perceived values. It is assumed that the perceived value of any given stimulus varies from moment to moment (and observer to observer) due to random processes, and forms a normal distribution on the underlying psychological continuum. The locations of the individual category boundaries also vary from moment to moment due to random processes, acting much like stimuli, each forming a normal distribution on the psychological continuum. The momentary values for a particular stimulus and for the criterion category boundaries determine the rating that will be assigned to that stimulus in a given instance.

The area under the theoretical normal distribution of perceived values for a given stimulus can be divided into the portion corresponding to the number (proportion) of times the stimulus is perceived to be higher on the dimension of interest than a given category boundary, and the remaining portion corresponding to the number (proportion) of times the stimulus is perceived to be lower than the given boundary. These proportions, in turn, can be translated to standard deviation units, or unit (standard) normal deviates (commonly referred to as Zs). The unit normal deviate corresponding to the proportion of times a stimulus is rated at or above a given rating category indicates the magnitude of the difference between the perceived value of the stimulus and the location of the lower boundary of that rating category on the underlying dimension. In other words, Thurstone's judgment scaling model assumes that differences in distances on the underlying psychological continuum are *proportional* to the unit normal deviates associated with the observed proportions (based on the ratings assigned).

[7] *Torgerson (1958) presents the Law of Catergorical Judgment in terms of the proportion of times a stimulus is perceived to be* below *the* upper *boundary of a given rating category. Torgerson's approach and the one presented here yield perfectly correlated scale values. The approach used here, which was also used by Daniel and Boster (1976), has the advantage of assigning* higher *scale values to the stimuli that were assigned higher ratings.*

In Thurstone's full model (Torgerson 1958), the difference between the perceived value of a stimulus and the location of a category boundary is:

$$C_k - S_i = \Phi^{-1}(CP_{ik})(\sigma_i + \sigma_k - 2r_{ik}\,\sigma_i\,\sigma_k)^{0.5} \quad [9]$$

where

- C_k = location of the lower boundary of the k^{th} category on the rating scale (e.g., the perceived scenic beauty value sufficient to meet the observer's standards for a rating of at least "8")
- S_i = scale value (e.g., perceived scenic beauty) of stimulus i
- CP_{ik} = proportion of times stimulus i is rated above the lower boundary of the k^{th} rating category
- Φ^{-1} = inverse normal integral function (which translates CP_{ik}, the cumulative proportion, to the appropriate unit normal deviate, Z)
- σ_i = dispersion (standard deviation) of the stimulus value distribution
- σ_k = dispersion of the category boundary distribution
- r_{ik} = correlation between positions of stimulus i and category boundary k.

Simplifying assumptions are necessary to apply Thurstone's model, because σ_i, σ_k, and r_{ik} are unknown and may be unique for any pairing of a stimulus and a category boundary, causing the standard deviation units in which each estimate of $C_k - S_i$ is expressed to also be unique. If we assume that C_k and S_i are normally distributed and independent for all k and i, so that $r_{ik} = 0$, and that σ_i and σ_k are unknown constants for all values of i and k, so that the variances of stimulus distributions and response criterion distributions are respectively homogeneous (Torgerson's "Condition D," 1958), [9] reduces to:

$$C_k - S_i = \Phi^{-1}(CP_{ik})\,\alpha \quad [10]$$

where α is an unknown constant[8] and $\Phi^{-1}(CP_{ik})$ is simply the standard normal deviate (Z) corresponding to the cumulative proportion CP_{ik}. As noted by Torgerson (1958) and Hull et al. (1984), these simplifying assumptions are generally tenable and greatly reduce computational complexity. Note that α can be assumed to be 1.0 since an interval scale is, in any case, determined only to within a linear transformation (both origin and interval are arbitrary).

The unit normal deviates (Zs) are computed for differences between S_i and each of the rating category boundaries (e.g., based on the proportion of times stimulus i is rated at or above a "7", an "8", etc.). Torgerson (1958) shows that, given a complete matrix of Zs and the simplifying assumptions mentioned above, the mean of the Zs averaged across the category boundaries is the best estimate of the scale value for a stimulus. This scale value (mean Z) indicates the average distance, in standard deviation units, of the perceived value of the stimulus from the different rating category boundaries.

[8] *α is the interval size of the theoretical scale on which the differences are measured, $(\sigma_i + \sigma_k - 2r_{ik}\,\sigma_i\,\sigma_k)^{0.5}$, which reduces to $(\sigma_i + \sigma_k)^{0.5}$ given the assumption that $r_{ik} = 0$.*

Mean Zs are computed for each stimulus. Given the necessary assumptions, the mean Zs indicate the relative positions of the stimuli on the underlying psychological continuum. So long as the mean rating category boundaries remain consistent across stimuli being rated, the *difference* between the perceived values for any two stimuli will be unaffected by the relative locations of the category boundaries.[9] The differences between stimuli are not affected by observers' rating (criterion) biases; whether observers choose to apply "strict" criteria (tending to assign low ratings to all stimuli) or "lax" criteria (tending to assign high ratings), the scaled differences between the stimulus values will be the same. Indeed, the stimulus differences will be the same even though entirely different ratings scales were applied (e.g., an 8-point scale versus a 10-point scale).[10] Moreover, the scaled differences between stimulus values will be the same regardless of how the category boundaries are arranged.[11] This feature of the Thurstone scaling procedures assures that the measure of stimulus differences can be interpreted as an equal-interval scale even though the category boundaries might not be equally spaced. Thus, if the necessary assumptions are met, ratings which may only achieve an ordinal level of measurement provide the basis for an interval scale measure of the perceived values of the stimuli.

In practice, Thurstone's model relies on multiple ratings for a stimulus to provide the proportions corresponding to the theoretical momentary locations of the perceived values of the stimuli and category boundaries. Ratings may be provided either by multiple observers who each rate the same stimuli or by a single observer who rates each stimulus a number of times. The normality and constant variance assumptions are perhaps most easily met in the case where a single observer provides all the necessary ratings (where replications of ratings of a given stimulus are provided by the same observer). In this case, as long as the observer is consistent with respect to the mean locations of the rating criterion boundaries and adheres to the independence and homogeneous variance expectations, the ratings are all based on the same set of boundaries. A practical problem with this case, however, is that it places a considerable burden on a single observer, who may become bored or otherwise affected by the requirement to rate the same stimuli again and again.

Scale values that are specific to individual observers can also be generated when stimuli are grouped into "conditions," as in Daniel and Boster's (1976) "by-

[9] *Note that $(C_k - S_i) - (C_k - S_{i+1}) = S_{i+1} - S_i$, and that this holds across all category boundaries (all C_k). That is, if the rating criterion boundaries are consistent, the Ck "drop out" and the differences between the scale values of the stimuli indicate differences in perceived value.*

[10] *This assumes, of course, that each scale has enough categories to allow for sufficiently fine distinctions among the perceived values of the stimuli. A 3-point scale, for example, would not generally allow for sufficient discrimination among a set of stimuli.*

[11] *This assumes, of course, that the categories are properly ordered, with each successive criterion signifying more (for example) of the underlying property being measured.*

observer'' SBE. ''Conditions'' are simply higher order stimuli that can each be represented to observers by multiple stimuli. Ratings of the stimuli within a condition provide the necessary replications as long as the conditions are each relatively homogeneous and the stimuli within a condition are randomly selected. As in the single observer case, this approach produces observer-specific scale values, such that each scale value only relies on one observer's set of rating criteria. However, because scale values are only produced for conditions (i.e., groups of stimuli), and not all objects of interest are easily represented by a sufficient number of randomly selected stimuli, this approach cannot always be applied.

The most commonly applied case is where each observer only rates each stimulus once and each stimulus is independent of all others. Here, the replications necessary for creating the rating distributions must be provided by combining ratings over multiple observers. Because each stimulus scale value is based on the rating criteria of multiple observers, it must be assumed that the constant mean and variance assumptions hold across observers. This assumption is more likely to be met if observers are randomly sampled from some relevant observer population, but it is a more stringent assumption than that required in the single-observer applications.[12]

By-Stimulus SBE

The ''by-stimulus'' option (Daniel and Boster's (1976) ''by-slide'' option) requires that multiple observers rate each stimulus. The by-stimulus procedure is generally used when only one or a few stimuli are available for each condition of interest, or when preference values are needed for each stimulus. In this procedure, a mean Z for each stimulus is computed based on the distribution of ratings assigned by the different observers. The cumulative proportion of observers judging the stimulus to be at or above each rating category is transformed to a Z by reference to the standard normal distribution. The Zs are then averaged over the rating categories to yield a mean Z for each stimulus. This procedure requires the assumption that perceived values of stimuli and rating criterion boundaries are normally distributed over the multiple observers.

[12]*Readers desiring a more thorough explanation of Thurstone's categorical judgment scaling model should consult Torgerson (1958), and examine the chapter on the Law of Comparative Judgment before going on to the chapter on the Law of Categorical Judgment.*

[13]*When this baseline is only used to set the origin of the SBE scale based on ratings obtained in one rating session, the stimuli comprising the baseline can be selected so that an SBE of zero indicates some specific condition. For example, in assessing the scenic beauty of forest areas managed under different harvest methods, this condition has often been the set of scenes sampled from an area representing the pretreatment state of the forest. However, when the SBEs of two or more rating sessions are to be compared, the baseline is also used to ''bridge the gap'' between ratings obtained in those different sessions. In this case, the baseline stimuli might best be selected to be representative of the full range of stimuli being rated, as described in the Psychological Scaling section.*

Individual mean Zs for each stimulus are further adjusted, following a procedure suggested by the Theory of Signal Detectability, to a common ''rational'' origin. A subset of the stimuli called a ''baseline'' is selected to determine the origin of the SBE scale.[13] The overall mean Z of the baseline stimuli is subtracted from the mean Z of each stimulus, and then the difference is multiplied by 100 (eliminating the decimals) to yield individual stimulus SBEs. As with any interval scale, of course, both the origin and interval size are arbitrary.

To summarize, the computation of the original (Daniel and Boster 1976) SBE for a stimulus requires three steps. First, the mean Z for each stimulus is computed as follows:

$$MZ_i = \frac{1}{m-1} \sum_{k=2}^{m} \Phi^{-1}(CP_{ik}) \qquad [11]$$

where

MZ_i = mean Z for stimulus i
Φ^{-1} = inverse normal integral function
CP_{ik} = proportion of observers giving stimulus i a rating of k or more
m = number of rating categories.

In step 2, the mean of the mean Zs of the stimuli composing the baseline condition is computed. In the last step, the mean Z of each stimulus is adjusted by subtracting the mean Z of the baseline, and the mean Z differences are multiplied by 100 to remove decimals:

$$SBE_i = (MZ_i - BMMZ)\ 100 \qquad [12]$$

where

SBE_i = SBE of stimulus i
MZ_i = mean Z of stimulus i
BMMZ = mean of mean Zs of the baseline stimuli.

Two conventions are used to facilitate computation of MZ_i in [11]. First, because all ratings of any stimulus must be at or above the lowest (e.g., the ''1'') category, so that CP_{ik} for the bottom rating category is always 1.0, the bottom category is omitted in the computation of MZ_i. Second, Thurstone's model only strictly applies where the distribution of ratings for a stimulus extends over the full range of the rating scale (i.e., where each stimulus is placed at least once in each criterion category). Where this does not occur (where $CP_{ik} = 1.0$ for rating categories at the low end of the scale or $CP_{ik} = 0$ for categories at the high end), $\Phi^{-1}(CP_{ik})$ is undefined. For these cases, we have adopted the convention proposed by Bock and Jones (1968) and adopted by Daniel and Boster (1976): for $CP_{ik} = 1.0$ and $CP_{ik} = 0$, substitute $CP_{ik} = 1\text{-}1/(2n)$ and $CP_{ik} = 1/(2n)$, respectively, where n is the number of observations (ratings) for each stimulus.[14]

[14]*For example, if n = 30, a cumulative proportion of 1.0 is set to 0.9833, and a cumulative proportion of 0 is set to 0.0167. The Zs of these cumulative proportions, like those of the other cumulative proportions, could then be obtained from a normal probability table. For example, the Z for a cumulative probability of 0.0167 is –2.13. Note that in many presentations of the normal probability table, only the upper half of the normal curve areas is tabulated. In such cases, the cumulative probability must be appropriately adjusted before using the table to determine the Z.*

A variation on the original SBE procedure is to also adjust the interval size of the SBE scale by dividing the original SBE by the standard deviation of the mean Zs of the baseline stimuli. For this variation, the SBE of equation [12] is adjusted to the interval size of the baseline to effect a standardization of the mean Zs:

$$SBE^*_i = SBE_i / BSDMZ \qquad [13]$$

where

SBE^*_i = standardized SBE of stimulus i
BSDMZ = standard deviation of mean Zs of baseline stimuli.

The combination of the origin and interval size adjustments effectively standardizes the SBEs to the baseline. This standardization is particularly useful where SBEs of different observer groups who have rated different nonbaseline stimuli are to be combined or otherwise compared. Although the computation of mean Zs, described above, theoretically creates an equal-interval scale, it does not assure that the scales of different groups of observers will have the same origin or interval size. The original SBE was designed to adjust for the possibility that different observer groups may differ in the origin of their scores. The full standardization of the mean Zs based on the ratings of the baseline stimuli is designed to adjust for the possibility that different observer groups may differ in the origin and/or interval size of their scores.

Table 4 depicts by-stimulus SBEs and associated ratings for four observer groups. The baseline of each set is the full set of stimuli. The ratings of all three observers within each of groups A, B, and E are perfectly correlated, although, as seen by examining the mean ratings, the interval sizes for each group are different. Examining the SBEs for these three data sets, we see that the origins of all three are identical (stimulus 3 of each set has an SBE of 0), but the interval sizes differ. Moving to the SBE*s, we see that the interval sizes among the three sets are now also identical, as would be expected following a standardization of the mean Zs to the baseline where the ratings of all observers of the three sets correlate perfectly. Thus, agreement (in absolute terms) between two observer groups' scale values is improved by adjusting for both origin and interval size differences. Of course, neither adjustment affects the linear association between the sets of scale values. It can also be seen by comparing observer groups B and D of table 4 that equal mean ratings between data sets does not necessarily lead to equal SBEs or SBE*s if the two sets of ratings are not perfectly correlated.

By-Observer SBE

The by-observer option requires that each observer provide multiple ratings of each condition (e.g., forest area) that is to be scaled. This may be accomplished by having each observer rate the same stimulus a number of times on different occasions. Usually, however, this is accomplished by having an observer rate a number of different stimuli representing each condition (e.g., different scenes from within the same forest area). The distribution of an individual observer's ratings of the

Table 4.—Ratings and by-stimulus SBEs for four observer groups.

Observer. . .		Rating			Scale value		
Observer group	Stimulus	1	2	3	Mean rating	SBE[a]	SBE*[a]
A	1	1	3	6	3.33	−43	−126
	2	2	4	7	4.33	−22	−63
	3	3	5	8	5.33	0	0
	4	4	6	9	6.33	22	63
	5	5	7	10	7.33	43	126
B	1	1	2	1	1.33	−86	−126
	2	3	4	3	3.33	−43	−63
	3	5	6	5	5.33	0	0
	4	7	8	7	7.33	43	63
	5	9	10	9	9.33	86	126
D	1	1	2	1	1.33	−87	−125
	2	2	6	2	3.33	−47	−68
	3	3	7	6	5.33	3	4
	4	5	8	9	7.33	46	66
	5	9	9	10	9.33	85	123
E	1	1	6	1	2.67	−62	−126
	2	2	7	3	4.00	−31	−63
	3	3	8	5	5.33	0	0
	4	4	9	7	6.67	31	63
	5	5	10	9	8.00	62	126

[a]*Baseline is the entire set of (i.e., all 5) stimuli.*

multiple stimuli for a condition is then used to derive a scale value for that condition. Individual observers' rating distributions are "normalized" by transforming the proportion of stimuli assigned to each rating category to the appropriate unit normal deviate, or Z. This procedure requires the assumption that ratings by an observer of the stimuli within a condition are sampled from an underlying normal distribution. Zs for each rating category are then averaged to yield a mean Z for each individual observer for each condition. These computations are summarized as follows:

$$MZ_{jc} = \frac{1}{m-1} \sum_{k=2}^{m} \Phi^{-1}(CP_{jck}) \qquad [14]$$

where

MZ_{jc} = mean Z of observer j for condition c
Φ^{-1} = inverse normal integral function
CP_{jck} = proportion of stimuli of condition c given a rating of k or more by observer j
m = number of rating categories.

The two conventions listed for [11] also apply to [14].

Individual observer mean Zs for each condition are then adjusted to the origin of a common baseline. Each observer's overall mean Z for the baseline condition(s) is subtracted from the mean Z for each of the conditions being assessed. The baseline condition is thus assigned a value of zero. The origin-adjusted mean Zs are then multiplied by 100 to yield individual observer SBEs for each condition:

$$SBE_{jc} = (MZ_{jc} - BMZ_j)\ 100 \qquad [15]$$

where

SBE_{jc} = SBE of observer j for condition c
MZ_{jc} = mean Z of observer j for condition c
BMZ_j = mean Z of observer j for the baseline.

Individual observer SBEs, adjusted to the same baseline, may then be averaged to derive an aggregate or group SBE value for each condition:

$$SBE_c = \frac{1}{n} \sum_{j=1}^{n} SBE_{jc} \qquad [16]$$

where

SBE_c = SBE for condition c
n = number of observers.

Note that the by-observer SBE described here is the same as the one presented by Daniel and Boster (1976), who provide a detailed example of the computation of by-observer SBEs. We do not introduce a variation to their procedure similar to the standardization variation presented above for the by-stimulus SBE. The by-observer computations do not offer a similar opportunity for standardization unless scores are combined across observers, and to combine across observers would eliminate a key feature of the by-observer procedure, which is individual interval scale scores for each observer.

Comparison of By-Stimulus and By-Observer SBEs

The principal difference between the two SBE procedures is in whether the final SBE index is derived from the distribution of ratings of multiple stimuli by a single observer, or from the distribution of ratings by multiple observers for a single stimulus. The by-observer procedure uses the distribution of ratings of multiple stimuli within a condition by one observer to derive that observer's SBE for that condition. In so doing, it is not possible to obtain an SBE measure for each stimulus; the variation among stimuli is used to derive the condition SBE. The by-stimulus procedure uses the distribution of ratings by multiple observers for a single stimulus to derive an SBE for that stimulus. By this procedure it is not possible to obtain an SBE measure for each observer; the variation among observers is used to derive the SBE for a stimulus. A condition SBE can be computed from stimulus SBEs by averaging over stimuli, however, if there is an adequate sample of stimuli to represent the condition.

The choice between the two SBE procedures typically is determined by the design of the assessment experiment. If a relatively small number of conditions, each represented by a number of different stimuli, are to be assessed, the by-observer procedure may be used. Usually at least 15 stimuli, randomly sampled from each condition, are required to make the normal distribution of stimulus ratings assumption tenable. If there are many conditions each represented by only one or a few stimuli, the by-stimulus procedure typically must be used. Usually at least 15 randomly assigned observers are required to meet the normal distribution of observer ratings assumption. When data having multiple observers and multiple stimuli for each condition have been analyzed by both the by-observer and the by-stimulus procedures, the resulting condition SBEs have typically been found to be essentially identical. In practice, situations allowing the by-observer procedure (i.e., where at least 15 randomly sampled stimuli are available to represent each condition assessed) have been relatively infrequent. But, in such situations, as long as at least 15 observers are used, the by-stimulus procedure can usually be applied with mathematically equivalent results.

Comparison of SBEs and Mean Ratings

The by-stimulus SBE is distinguished from the mean rating of [1] by the transformation to standard normal deviates. This is shown by recognizing the relationship between the mean rating and the sum of the proportions of ratings in each rating category:

$$MR_i = \frac{1}{m} \sum_{k=1}^{m} k\ P_{ik} \qquad [17]$$

where

MR_i = mean rating of stimulus i
P_{ik} = proportion of observers giving stimulus i a rating of k
m = number of rating categories.

Thus, the important difference between the mean rating of [1] (MR_i) and the mean Z of [11] (MZ_i) is that in the mean rating the proportion (P_{ik}) is weighted by the rating value (k), while in the mean Z the cumulative proportion (CP_{ik}) is weighted by the inverse normal integral function (Φ^{-1}). Other differences between the mean rating and the SBE, the standardization to the baseline and multiplication by 100 in [12], merely cause a linear transformation.

To compare mean ratings of stimuli judged during a given session, one must assume that on average the group's rating criterion scale is equal interval, plus of course that the rating criterion scale is consistent for the duration of the rating session. To compare mean ratings of two different observer groups, we must also assume that the rating criterion scales of the two groups are identical. But to use SBEs to compare stimuli within a group or to compare across groups, we need to assume (in addition to the normality and independence assumptions) only that raters, on average, were each consistent in use of their individual rating criterion scales for the duration of the rating session.

Comparison of SBEs With Z-Scores and LSRs

SBEs may be distinguished from Z-scores in several ways. First, individual Z-scores are directly *computed* from the ratings assigned to each stimulus by each observer. In the by-observer SBE procedure, the Zs are derived from the *distribution* of ratings by one observer over the multiple stimuli within a condition. The proportions (actually cumulative proportions) of the stimuli within a condition that are assigned to each rating category are transformed to Zs using the inverse normal integral function, assuming that those ratings are sampled from a normal distribution.

In the by-stimulus SBE procedure, the Zs are derived from the distribution of multiple observers' ratings of an individual stimulus. The proportion of observers assigning a given rating category to the stimulus is transformed to a Z, assuming that the set of observer ratings was sampled from a normal distribution within the relevant population of observers. Because these Zs depend upon the distribution of different observers' ratings for one stimulus, they cannot be directly compared with the Z-scores computed for a single observer over multiple stimuli. Of course, if the ratings of all observers of a data set are perfectly correlated, the baseline-adjusted mean Z-scores will be identical to the by-stimuli SBE*s, except for the decimal point which is two places to the right in the SBE*. And, if the baseline is the full set of stimuli, the mean Z-scores will be identical to the SBE*s, except for the decimal point, as can be seen by comparing tables 2 and 4 for observer groups A, B, and E. Furthermore, under the condition of perfectly correlated ratings, mean Z-scores differ from mean LSRs only by their origin (grand mean rating) and interval size (standard deviation of mean ratings), and mean LSRs are identical to mean ratings. That is, if ratings of all observers within a group are perfectly correlated, and if the baseline is the entire set of stimuli,

$$SBE^*_i/100 = MZ_i = (LSR_i - MMR)/SDMR = (MR_i - MMR)/SDMR \quad [18]$$

where

SBE^*_i = standardized SBE of stimulus i
MZ_i = mean Z-score of stimulus i
LSR_i = mean least squares rating of stimulus i
MMR = mean of the mean ratings assigned to all stimuli by all observers in the group (grand mean rating)
SDMR = standard deviation of the mean ratings assigned by all observers in the group
MR_i = mean rating assigned to stimulus i.

Of course, the ratings of all observers are rarely perfectly correlated, so the relationship between SBE*s, Z-scores, LSRs, and ratings will be more complex, as can be seen by comparing tables 2, 3, and 4 for observer group D. Theoretically, the SBE metrics would be preferred because they do not require the assumption that observers' ratings constitute an equal-interval scale. Indeed, as Torgerson (1958), Green and Swetts (1966), and others have shown, SBE-type metrics computed for reasonable-sized groups of observers will be quite robust to substantial violations of the formal distribution assumptions.

Summary

The information presented above about the various procedures available in RMRATE for scaling rating data is summarized here in two ways. First, we review which procedures address the potential problems with interpreting rating data. Second, we discuss when to use each of the procedures.

Scaling Procedures and the Interpretation of Ratings

In the "Psychological Scaling" section, several potential problems with interpreting rating data were described, which, to the extent they exist for a given set of ratings, limit inferences that can be drawn about the perceptions of the stimuli being rated. Two of those problems, lack of intraobserver consistency and perceptual or criterion shifts, can only be addressed by proper experimental design, which is outside the scope of this paper. The other potential problems can all be reduced or avoided by employing a proper scaling procedure. Those problems are listed in table 5.

An X in table 5 indicates that the respective scaling procedure somehow addresses the potential problem. Median and mean ratings do not address any of the identified problems. The OAR adjusts for differences in criterion scale origin, but not interval size differences. The Z-score procedures adjust for both origin and interval differences in criterion scales, assuming that each observer is using an equal-interval criterion scale. Thus, if it is important to adjust for linear differences between

Table 5.—Which scaling procedures address potential problems of rating data?

Scaling procedure	Potential problems					
	Unequal-interval scale	Linear differences between observers' criterion scales		Linear differences between groups' criterion scales		Lack of interobserver correspondence (aside from linear differences)
		Origin size	Interval	Origin size	Interval	
Median rating						
Raw ratings						
OAR		X				
BOAR		X		X		
Z-score		X	X			
BZ-score		X	X	X	X	
LSR		X	X			X
BLSR		X	X			X
By-stimulus SBE	X			X		
By-stimulus SBE*	X			X	X	
By-observer SBE	X	X	X	X		

observers or observer groups, the Z-score procedures would be preferred over raw ratings and OARs.

The LSR procedures also adjust for linear differences between observers within a group, and in addition weight each observer's ratings by how well the observer agrees with the group. However, this scaling method does not adjust for linear differences between groups. If weighting based on fit with the group is desired, and ratings of separate groups are not going to be compared on an absolute basis, the least squares rating would be preferred over the Z-score procedures.

Only the SBE procedures adjust for unequal interval judgment criterion scales. This advantage is obtained at the expense of combining ratings over observers or stimuli, so that individual scale values (for each stimulus by each observer) are not obtained. All three SBE procedures adjust for origin differences among observer groups, but only the by-stimulus SBE* adjusts for interval size differences among groups.

Which Procedure To Use When

Choice of the most appropriate psychological scaling procedure for any given application will depend upon the design of the scaling experiment, the goals of the measurement task, and the extent to which the investigator is willing to accept the assumptions of each scaling procedure. If the resulting scale values are to be used for only ordinal comparisons, no assumptions are necessary about the nature of the rating scale. In this case, the median is probably the appropriate scaling procedure, since the others would entail needless complexity for the task at hand. If the scale values are to be used as interval measures (which is required for most standard statistical operations), choosing among the mean rating, computed Z-score, LSR, and SBE procedures will depend primarily upon the assumptions the investigator is willing to make about the data, and upon the desired features for the final scale. The mean rating and LSR procedures produce scale values in terms of the original rating scale, while the Z-score and SBE procedures produce scale values that are not easily interpreted in terms of the original scale. There is no absolute meaning to the rating values, so maintaining the scale values in terms of the original rating scale is only cosmetic. Nevertheless, it may be easier to explain results to some audiences in terms of rating points.

The mean ratings, Z-scores, and LSRs assume that each group of observers used an equal-interval scale for rating the stimuli. The SBE procedure does not require that observers or groups use equal-interval scales; it assumes only that rating criteria are consistent over a rating session, and that (for by-observer SBE) ratings by an observer of the stimuli within a condition are normally distributed, or (for the by-stimulus SBE) the ratings of each stimulus by all observers are normally distributed.

If the assumption that ratings of a stimulus over multiple observers are normally distributed is valid, or at least more tenable than the assumption that each observer's ratings represent an interval scale, then the by-stimulus SBE procedure is a good choice. The SBE procedure also provides a standard scale, irrespective of the number of categories in the original rating scale, that has been shown in theory and practice to be comparable to scales derived by other psychophysical procedures (e.g., paired-comparisons and rankings). A possible disadvantage of the by-stimulus SBE procedure is that scale values are not provided for individual observers.

The Z-score procedure is widely used for transforming distributions to a standard form and is computationally straightforward. A possible disadvantage is that individual observer's ratings are transformed separately, without regard to how other observers in the group rated the same stimuli. Assuming a linear relationship among observers' ratings, the least squares procedure "fits" each observer's ratings to the mean ratings assigned by the entire group of observers, thus providing individual scale values for each observer that depend on the relationship with the group ratings. The final scale,

however, is dependent on the number of categories in the original rating scale and thus cannot be directly compared (or combined) with scales derived from other rating scales, or other psychological scaling procedures. Also, the least squares procedure incorporates a differential weighting of observers, which reduces the natural variation in the ratings, in essence placing more credence on some observers than others, and may be contrary to the goals of the assessment.

Unlike the SBE procedures, the Z-score and least squares procedures each provide individual scores for each observer for each stimulus, a feature that has some important practical advantages. Individual observer's scales can be inspected for internal consistency as well as for consistency with other observers in the same assessment. Further, the Z-score and LSR procedures, like the raw ratings, preserve degrees of freedom for subsequent analyses, such as analysis of variance to compare stimuli or conditions, or correlation and regression analyses involving other measures available for the stimuli. Having individual observer values for each stimulus also facilitates the computation of conventional measures of the error of estimate for individual stimuli (such as the standard error of the mean) based on the variability in scores among observers. Of course, this advantage is gained at the expense of assuming the individual ratings represent an interval scale of measurement.

If different observers rate different subsets of the stimuli and rate one subset in common, then one of the baseline procedures will be most appropriate. The resulting scale will have an origin (for the baseline-adjusted OAR and the SBE) or an origin and interval size (for the baseline-adjusted Z-score and the SBE*) determined by the ratings of the baseline stimuli.

Except perhaps for the median, all of these scales generally produce sets of scale values for a set of stimuli that correlate greater than 0.90 with each other when individual scale values are averaged or otherwise combined over at least 15 observers to produce a group index (see Schroeder 1984). However, when different observers have used explicitly different rating scales, or when individual differences between observers or differences in the contexts in which stimuli have been rated are substantial (e.g., Brown and Daniel 1987), some transformation of the original scale is required.

There are also theoretical reasons for choosing a transformed scale. The goal of the different scaling procedures is to provide estimates of the locations and distances between objects on the inferred psychological dimension. RMRATE (Brown et al. 1990) provides the investigator a choice among, and the opportunity to compare, several psychological scaling procedures that approach this goal somewhat differently.

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APPENDIX

RELATIONSHIPS AMONG SCALE VALUES

Here we review relationships among the scaling procedures by comparing the results of using each procedure to scale ratings from several hypothetical observer groups. Table A1 lists scale values of seven scaling procedures for five hypothetical observer groups, each assumed to have rated the same five stimuli. The baseline for the SBE is the entire set of five stimuli for each data set.

Observers of group A differ only in the origin of their ratings. Thus, the origin-adjusted ratings (OARs) of the three observers in the group are identical. Likewise, the Z-scores of the three observers are identical, as are their least squares ratings (LSRs). Furthermore, notice that the mean ratings and mean LSRs are identical.

Group B, like group A, contains observers who differ only in the origin of their ratings. However, groups A and B differ in the interval size of their respective ratings, with observers of group B using a larger rating difference than observers of group A to draw distinctions among the same stimuli. For example, observers of group A use a rating difference of 1 to distinguish between stimulus 1 and stimulus 2, while observers of group B use a rating difference of 2 to make this distinction. Thus, the mean OARs of these two data sets differ, as do the mean LSRs, but the mean Z-scores of the two sets are identical.

Group E contains observers whose ratings differ from each other in both origin and interval size. Thus, the OARs are different between observers who differ in interval size (observer 3 versus observers 1 and 2). However, because the ratings of the three observers are perfectly linearly related, the Z-scores of all three observers are identical, the LSRs of the three observers are identical, and the mean ratings, mean OARs, mean Z-scores, mean LSRs, and SBEs are perfectly linearly related. Furthermore, because the ratings of observers of group E are perfectly linearly related to those of observers of groups A and B, the Z-scores of all observers of these three data sets are identical, as are the mean Z-scores.

The SBE*s of observer groups A, B, and E are identical, again because the ratings of the observers of each group are perfectly correlated. Furthermore, because of this, the SBE*s are identical to the mean Z-scores (except for the placement of the decimal point). Group F differs from group B in that observer 3's ratings in group F are monotonically related to but not perfectly correlated with those of observers 1 and 2. This difference has the following effects. First, the OARs, Z-scores, and LSRs of observer 3 are not identical to those of observers 1 and 2. Second, mean Z-scores and SBE*s of group F differ from those of group B. Third, the mean Z-scores and SBE*s of group F differ (by more than the decimal point shift) and, in fact, are no longer perfectly correlated.

The ratings of observers of group D are monotonic but not perfectly correlated. Thus, the OARs of the three observers differ, as do the Z-scores and LSRs of the three observers. Furthermore, the mean ratings, mean Z-scores, mean LSRs, and SBEs are not perfectly linearly related (although the SBEs are perfectly linearly related to the SBE*s). Note, however, that the mean ratings and mean OARs of group D are identical to those of group B. Again, identical mean ratings do not necessarily produce identical Z-scores, LSRs, or SBEs.

Comparisons for Data Sets With a Common Baseline

Table A2 contains ratings for five hypothetical observer groups. The groups are assumed to have each been randomly selected from the same observer population and to have each rated sets of eight stimuli, each set containing three common baseline stimuli (indicated by a "B") and five unique stimuli. The nonbaseline ratings of observer groups II, III, IV, and V are identical, but the baseline ratings of the four groups differ. The nonbaseline ratings of group I differ from those of the other groups, but the baseline ratings of groups I and II are identical. Assuming that the baseline stimuli of the five data sets are identical, but the nonbaseline stimuli of the sets are unique, baseline adjustments would facilitate comparison across the sets.

The baseline ratings of observer groups I and II of table A2 are identical, but the nonbaseline ratings are not. However, the nonbaseline ratings of the two groups are perfectly correlated, differing only in interval size. As-

Table A1.—Comparison of scale values for five observer groups.

		Rating			OAR			Z-score			LSR			Scale value						
Observer . . .		1	2	3	1	2	3	1	2	3	1	2	3							
Observer group	Stimulus													Median	Mean rating	Mean OAR	Mean Z-score	Mean LSR	By-stimulus SBE[a]	By-stimulus SBE*[a]
A	1	1	3	6	−2.0	−2.0	−2.0	−1.26	−1.26	−1.26	3.33	3.33	3.33	3	3.33	−2.00	−1.26	3.33	−43	−126
	2	2	4	7	−1.0	−1.0	−1.0	−.63	−.63	−.63	4.33	4.33	4.33	4	4.33	−1.00	−.63	4.33	−22	−63
	3	3	5	8	.0	.0	.0	.00	.00	.00	5.33	5.33	5.33	5	5.33	.00	.00	5.33	0	0
	4	4	6	9	1.0	1.0	1.0	.63	.63	.63	6.33	6.33	6.33	6	6.33	1.00	.63	6.33	22	63
	5	5	7	10	2.0	2.0	2.0	1.26	1.26	1.26	7.33	7.33	7.33	7	7.33	2.00	1.26	7.33	43	126
B	1	1	2	1	−4.0	−4.0	−4.0	−1.26	−1.26	−1.26	1.33	1.33	1.33	1	1.33	−4.00	−1.26	1.33	−86	−126
	2	3	4	3	−2.0	−2.0	−2.0	−.63	−.63	−.63	3.33	3.33	3.33	3	3.33	−2.00	−.63	3.33	−43	−63
	3	5	6	5	.0	.0	.0	.00	.00	.00	5.33	5.33	5.33	5	5.33	.00	.00	5.33	0	0
	4	7	8	7	2.0	2.0	2.0	.63	.63	.63	7.33	7.33	7.33	7	7.33	2.00	.63	7.33	43	63
	5	9	10	9	4.0	4.0	4.0	1.26	1.26	1.26	9.33	9.33	9.33	9	9.33	4.00	1.26	9.33	86	126
D	1	1	2	1	−3.0	−4.4	−4.6	−.95	−1.63	−1.14	2.48	.51	1.81	1	1.33	−4.00	−1.24	1.60	−87	−125
	2	2	6	2	−2.0	−.4	−3.6	−.63	−.15	−.89	3.43	4.89	2.57	2	3.33	−2.00	−.56	3.63	−47	−68
	3	3	7	6	−1.0	.6	.4	−.32	.22	.10	4.38	5.99	5.64	6	5.33	.00	.00	5.34	3	4
	4	5	8	9	1.0	1.6	3.4	.32	.59	.84	6.28	7.09	7.94	8	7.33	2.00	.58	7.10	46	66
	5	9	9	10	5.0	2.6	4.4	1.58	.96	1.09	10.08	8.18	8.71	9	9.33	4.00	1.21	8.99	85	123
E	1	1	6	1	−2.0	−2.0	−4.0	−1.26	−1.26	−1.26	2.67	2.67	2.67	1	2.67	−2.67	−1.26	2.67	−62	−126
	2	2	7	3	−1.0	−1.0	−2.0	−.63	−.63	−.63	4.00	4.00	4.00	3	4.00	−1.33	−.63	4.00	−31	−63
	3	3	8	5	.0	.0	.0	.00	.00	.00	5.33	5.33	5.33	5	5.33	.00	.00	5.33	0	0
	4	4	9	7	1.0	1.0	2.0	.63	.63	.63	6.67	6.67	6.67	7	6.67	1.33	.63	6.67	31	63
	5	5	10	9	2.0	2.0	4.0	1.26	1.26	1.26	8.00	8.00	8.00	9	8.00	2.67	1.26	8.00	62	126
F	1	1	2	1	−4.0	−4.0	−3.0	−1.26	−1.26	−.95	1.07	1.07	2.10	1	1.33	−3.67	−1.16	1.41	−80	−119
	2	3	4	2	−2.0	−2.0	−2.0	−.63	−.63	−.63	3.03	3.03	3.07	3	3.00	−2.00	−.63	3.04	−43	−64
	3	5	6	3	.0	.0	−1.0	.00	.00	−.32	5.00	5.00	4.03	5	4.67	−0.33	−.11	4.68	−6	−9
	4	7	8	5	2.0	2.0	1.0	.63	.63	.32	6.97	6.97	5.97	7	6.67	1.67	.53	6.63	37	55
	5	9	10	9	4.0	4.0	5.0	1.26	1.26	1.58	8.93	8.93	9.83	9	9.33	4.33	1.37	9.23	92	137

[a]*Baseline is the entire set of (i.e., all 5) stimuli.*

suming that the nonbaseline stimuli in each set did not affect the ratings of the baseline stimuli (i.e., assuming that there is no interaction between the ratings of the baseline and nonbaseline stimuli), the identity of the baseline ratings of the two data sets suggests (but of course does not prove) that the observers of the two groups perceive the stimuli equally and use identical judgment criteria. Thus, assuming equal-interval scales, and given the psychometric model, the mean ratings of the two groups could reasonably be assumed to be directly comparable. The baseline-adjusted metrics (BOAR, BZ-score, BLSR, and SBE*) would then also be assumed to be directly comparable. For example, using SBE*s, stimulus 1 (rated by group I) would be considered as different from stimulus 3 as stimulus 7 (rated by group II) is from stimulus 8, since both differences are indicated by an SBE* difference of 200. However, the procedures that generate scale values from a combination of the baseline and nonbaseline ratings (the mean OAR, mean Z-score, and mean LSR) would produce scale values that are not directly comparable across data sets; the basis of comparison must be only the set of common (i.e., baseline) stimuli.

Although the nonbaseline ratings of observer groups II and III are identical, the baseline ratings of the two sets differ in terms of *origin* (baseline ratings of group III have a higher origin than those of group II). This simple difference in ratings of the baseline stimuli suggests (given the psychometric model) that the two observer groups used different rating criterion scales, and that the identity of the ratings of the nonbaseline stimuli is fortuitous. The mean ratings of the two sets are identical, because the mean rating computation does not use the baseline ratings. Given the baseline ratings of the two sets, we would be in error to assume that the mean ratings of the two sets are directly comparable (e.g., to conclude that stimulus 7 is identical, or nearly so, to stimulus 12 on the underlying dimension).

The baseline-adjusted mean OARs of observer groups II and III, however, can more reasonably be compared (again, assuming equal-interval ratings and the psychometric model) because the baseline OAR procedure adjusts for origin differences among sets that have a common baseline, and, as we have seen, the two sets differ only in origin of the rating scale. A similar logic applies to the SBE (except that the assumption of equal-interval ratings is not needed). In addition, the mean baseline-adjusted Z-scores and SBE*s are comparable across the two groups, because these procedures also adjust for origin differences in the baseline ratings. All these metrics (mean BOAR, mean BZ-score, SBE, and SBE*) indicate, for example, that stimulus 6 is considered equidistant between stimuli 11 and 12 on the underlying dimension. But the mean OARs, or the mean Z-scores, of the two sets are not comparable, because the individual OAR or Z-score transformations are based on the ratings of all the stimuli, including the nonbaseline stimuli. Also, note that the SBE*s of each of the groups are identical to the mean baseline-adjusted Z-scores of the groups, except for the decimal point. This occurs be-

Table A2.—Comparison of scale values for five observer groups that rated sets of baseline and unique stimuli.

Observer group	Stimulus	Rating 1	Rating 2	Rating 3	Scale value: Median	Mean rating	Mean OAR	Mean BOAR	Mean Z-score	Mean BZ-score	Mean LSR	Mean BLSR	By-stimulus SBE	By-stimulus SBE*
I	1	1	3	6	3	3.33	−2.00	−2.00	−1.53	−2.00	3.33	3.33	−43	−200
	2	2	4	7	4	4.33	−1.00	−1.00	−.76	−1.00	4.33	4.33	−22	−100
	3	3	5	8	5	5.33	.00	.00	.00	.00	5.33	5.33	0	0
	4	4	6	9	6	6.33	1.00	1.00	.76	1.00	6.33	6.33	22	100
	5	5	7	10	7	7.33	2.00	2.00	1.53	2.00	7.33	7.33	43	200
	B1	2	4	7		4.33								
	B2	3	5	8		5.33								
	B3	4	6	9		6.33								
II	6	1	2	1	1	1.33	−4.00	−4.00	−1.48	−4.00	2.04	1.33	−86	−400
	7	3	4	3	3	3.33	−2.00	−2.00	−.73	−2.00	3.72	3.33	−43	−200
	8	5	6	5	5	5.33	.00	.00	.01	.00	5.40	5.33	0	0
	9	7	8	7	7	7.33	2.00	2.00	.76	2.00	7.08	7.33	43	200
	10	9	10	9	9	9.33	4.00	4.00	1.51	4.00	8.76	9.33	86	400
	B1	2	4	7		4.33								
	B2	3	5	8		5.33								
	B3	4	6	9		6.33								
III	11	1	2	1	1	1.33	−4.38	−5.00	−1.60	−5.00	2.01	1.33	−107	−500
	12	3	4	3	3	3.33	−2.38	−3.00	−.85	−3.00	3.74	3.33	−64	−300
	13	5	6	5	5	5.33	.00	−1.00	−.11	−1.00	5.48	5.33	−21	−100
	14	7	8	7	7	7.33	2.00	1.00	.64	1.00	7.21	7.33	21	100
	15	9	10	9	9	9.33	4.00	3.00	1.39	3.00	8.95	9.33	64	300
	B1	3	5	8		5.33								
	B2	4	6	9		6.33								
	B3	5	7	10		7.33								
IV	16	1	2	1	1	1.33	−4.00	−4.00	−1.53	−2.00	1.33	1.33	−86	−200
	17	3	4	3	3	3.33	−2.00	−2.00	−.76	−1.00	3.33	3.33	−43	−100
	18	5	6	5	5	5.33	.00	.00	.00	.00	5.33	5.33	0	0
	19	7	8	7	7	7.33	2.00	2.00	.76	1.00	7.33	7.33	43	100
	20	9	10	9	9	9.33	4.00	4.00	1.53	2.00	9.33	9.33	86	200
	B1	3	4	3		3.33								
	B2	5	6	5		5.33								
	B3	7	8	7		7.33								
V	21	1	2	1	1	1.33	−3.88	−3.67	−1.49	−2.00	1.36	1.31	−79	−204
	22	3	4	3	3	3.33	−1.88	−1.67	−.72	−.91	3.35	3.32	−36	−93
	23	5	6	5	5	5.33	.13	.33	.05	.18	5.33	5.33	7	19
	24	7	8	7	7	7.33	2.13	2.33	.82	1.27	7.32	7.34	50	130
	25	9	10	9	9	9.33	4.13	4.33	1.58	2.36	9.30	9.35	93	241
	B1	2	4	3		3.00								
	B2	5	6	5		5.33								
	B3	6	8	6		6.67								

cause the ratings of all observers within each of the groups are perfectly correlated.

Now examine the ratings of groups II and IV. As in the previous comparison (of groups II and III), the ratings of the nonbaseline stimuli of groups II and IV are identical. However, the baseline ratings of these two groups differ in *interval* size, such that a difference of 1 in group II's baseline ratings appears to be equivalent to a difference of 2 in group IV's baseline ratings. The mean ratings of groups II and IV are identical, but, as before, the baseline ratings suggest a difference in criterion scales and that the identity in nonbaseline ratings is misleading. The baseline-adjusted OARs of the two sets are also identical, as are the SBEs of the two sets, but these scale values are not comparable between sets, because the OAR and SBE procedures do not adjust for interval size differences between sets of baseline ratings. Only the baseline-adjusted Z-scores and SBE*s of the two sets could (given the psychometric model) reasonably be assumed to be comparable, because these two procedures adjust for interval size differences between sets of baseline ratings.

Next, consider the ratings of observer groups I and IV. Ratings of all observers of group I, including those of the baseline, are perfectly correlated with those of observers of group IV, but (as seen by examining the rat-

ings for the baseline stimuli) the ratings of the two data sets differ in interval size. The mean ratings of the baseline stimuli suggest that a rating difference of 1 was used by group I to indicate the same difference between stimuli as a rating difference of 2 by group IV. The mean ratings of the stimuli of the two groups differ, as do the mean OARs. The mean Z-scores of the two groups are identical, because all ratings of the two sets are perfectly correlated. Likewise, the baseline-adjusted mean Z-scores of the two sets are identical. However, the mean Z-scores of each group are not identical to the baseline-adjusted mean Z-scores, because the mean and standard deviation for the standardization are computed from all the ratings for the mean Z-score and just from the baseline ratings for the baseline-adjusted mean Z-score. The mean LSRs of the two data sets differ, as do the mean baseline-adjusted LSRs, because the least squares procedures do not adjust for linear differences between data sets. Finally, the SBEs of the two observer groups are different, but the SBE*s of the two groups are identical, and are equal to the baseline-adjusted mean Z-scores, except for the decimal point, because the two sets of ratings are perfectly correlated and the latter two procedures adjust for interval size differences across sets of baseline stimuli.

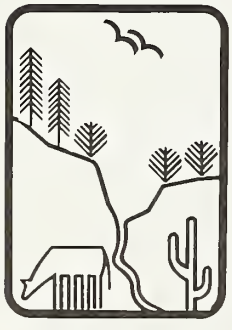
The nonbaseline ratings of observer group V are identical to those of groups II, III, and IV, but the baseline ratings of group V are neither identical to nor perfectly correlated with those of the other groups. Because the Z-score, least squares, and SBE procedures all utilize the baseline ratings in the computation of their respective scale values, for each procedure the scale values of group V are not perfectly correlated with those of the other groups. For example, the correlations of the SBE*s of group V to those of groups II, III, and IV are less than 1.0. Furthermore, the scale values produced by the Z-score, least squares, and SBE scalings of group V's ratings are not perfectly correlated with each other, or with the mean ratings. Each procedure deals with the lack of correlation in a different way. Only the SBEs and SBE*s can be perfectly correlated, because one is a simple linear transformation of the other.

Brown, Thomas C.; Daniel, Terry C. 1990. Scaling of ratings: concepts and methods. Res. Pap. RM-293. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Forest and Range Experiment Station. 24 p.

Rating scales provide an efficient and widely used means of recording judgments. This paper reviews scaling issues within the context of a psychometric model of the rating process, describes several methods of scaling rating data, and compares the methods in terms of the assumptions they require about the rating process and the information they provide about the underlying psychological dimension being assessed.

Keywords: Ratings, psychological scaling, measurement, judgment scaling model

Rocky Mountains



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